TRACKING FOR WORKER SAFETY ASSESSMENT

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TRACKING FOR WORKER SAFETY ASSESSMENT

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Dedicated to my family for their love, endless support, and sacrifices

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LIST OF SYMBOLS AND ABBREVIATIONS

2D	Two-Dimensional
3D	Three-Dimensional
BIM	Building Information Modeling
BLE	Bluetooth low-energy
CDF	Cumulative Distribution Function
CPWR	Center to Protect of Worker Right
dBm	Decibel-milliwatts
FN	False Negative
FP	False Positive
GPS	Global Positioning System
IMU	Inertial Measurement Unit
K-NN	K-Nearest Neighborhood
ms	Millisecond
MLE	Maximum Likelihood Estimation
OSHA	Occupational Safety and Health Administration
PDF	Probability Distribution Function
PLS	Probability Local Search
RF	Radio Frequency
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indication
RTLS	Real Time locating System
SPI	Safety Performance Index

TN	True Negative
TP	True Positive
UWB	Ultra-Wide band
ZBSR	Zone-based Safety Risk

SUMMARY

Despite exercising current safety practices, the construction industry has not been successful at protecting workers. Because of a dearth of effective methods for data collection, the construction industry has relied on human manual efforts, which are subjective, ineffective, and inconsistent. Furthermore, because of inadequately performed data collection and safety management process, evaluations of safety performance on a project are conducted mostly at the process or project level, not the individual level. As such data/information is not available, our understanding of individual workers' safety performance and the overall safety performance of the project remains limited.

The main objective of this dissertation is to develop a framework and methods for automate on-site data collection and safety performance evaluation of individual workers. It introduces two tracking-methodological developments and a method for assessing the safety performance of workers using tracking data. To this end, the study presents an integrated system of safety assessment that 1) uses the developed tracking module to automatically collect individual contextual data from the site, 2) analyzes these data together with pre-identified hazard data, and 3) evaluates the safety performance of individual workers. The scope of the work is limited to zone-based hazardous situations. It does not include hazards to workers while they are on the job (e.g., cutting fingers, falling from a ladder, equipment operation mistakes, electrocution). The findings of the study contribute to the body of knowledge in several ways: The proposed algorithmic development shows an effective method for indoor tracking; the safety procedural developments bridge on-site data collection and safety analysis processes; and, the safety

performance index data provide safety-related information on an unprecedented level that has not been available in the industry. Thus, by augmenting our knowledge and understanding of worker safety, the developed methods should be of value to both researchers and practitioners.

CHAPTER 1. INTRODUCTION

CHAPTER 1 introduces an overview of job safety, related current practices, and related previous research that has explored advanced technology for developing applications in construction. This chapter identifies existing challenges and drawbacks of current practices and previous research and then derives research/knowledge gaps that form the basis of this dissertation.

1.1 Overview

In recent years, one of the biggest challenges that the construction industry has struggled with is safety. In 2014, 899 occurrences of worker fatalities were recorded in construction, which is about 20 percent of worker fatalities in private industry in 2014 (Occupational Safety & Health Administration (OSHA) 2015). From the Center for Construction Research and Training, also known as Center to Protect Worker Rights (CPWR 2013), other statistics indicate that the recorded fatality rate of the construction industry in the United States is 9.7 deaths per 100,000 full-time workers. Compared with the rates in the other industries, ranging from 3.3 to 10.6 deaths per 100,000 workers, this rate is considered high; the high fatality rate of the construction industry explains 17.1 percent of total deaths in the United States in 2010—802 cases out of 4690 cases (Figure 1). Although safety is one of the top priorities in construction, the industry has not been successful at protecting workers by exercising current safety practices.

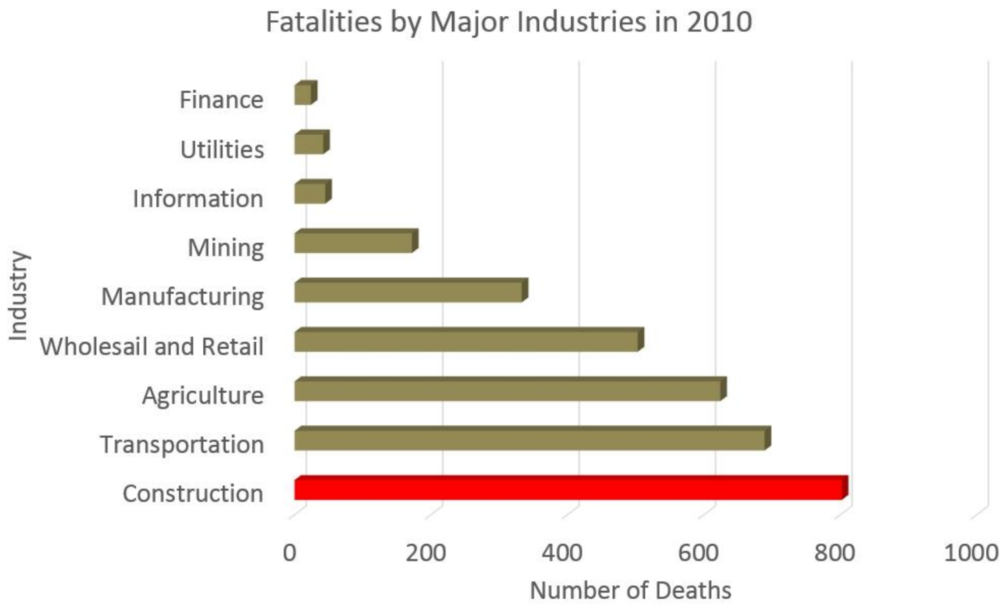


Figure 1: Fatalities in major industries, 2010 (CPWR 2013)

1.2 Safety Practices

The construction industry still relies on human manual effort, which is subjective, ineffective, and inconsistent in the safety management process. Because of these challenges, most safety performance evaluations are conducted/collected at a project or process level, and thus our understanding of safety performance of individual workers still remains limited, hampering more comprehensive analysis. For example, one of the most common safety performance measures, which is manually recorded statistical data, is passive and unable to provide immediate site information at an individual level. Another limitation of manual site observation at a construction site is ineffectiveness, which results in subjective decisions and inconsistent records. In addition, this method suffers from difficulty in identifying hazards in a dynamically and constantly evolving construction field environment, leaving a big portion of hazards unidentified and thus unanalyzed. Researchers have not yet addressed these limitations properly by state-of-the-art safety monitoring technologies. Methods using such technologies for progressively collecting site information/data for evaluating the safety condition of workers are lacking. Therefore, the construction industry requires a novel, integrated approach that collects on-site data, interprets the data with respect to identified safety hazards, and evaluates the safety performance at an individual worker level in a more interactive manner.

1.3 Advanced Technology in Construction

Construction projects are dynamic and complex in nature and large in size. In addition, each construction project is uniquely designed, and the combinations of construction operations are diverse. This trend has been more evident over the last decade, which led to additional challenges in various aspects of construction (Park et al. 2016a; Shahi et al. 2012). As an assisting tool to overcome these challenges, sensing and information technologies have gained in popularity in recent years. Sensing and information technologies have made unprecedented advancements, and many researchers have investigated these technologies to develop innovative tools to assist in construction operations from design to management.

Along with this research effort, many outdoor applications have been explored with various sensing technologies. For example, researchers explored video cameras by using captured images or video frames as a detection method: Worker tracking (Park et al. 2011; Park and Brilakis 2012) and quality control (Leung et al. 2008). On the other hand, inertial measurement units (IMU) were used to collect bodily responses to identify the relationship between the bodily reactions of a worker and to detect fall hazards (Kim et al. 2016a; Yang et al. 2015). Radio-frequency-identification (RFID) is another popular sensing technology. Researchers (Marks and Teizer 2013; Park et al. 2015) used RFID as a proximity detection and alert system to prevent colliding accidents between workers and equipment. In addition, other researchers integrated RFID (or similar radio frequency (RF)-based technology) with other sensing technologies, such as global positioning system (GPS) and ultrasound, and developed approaches for tracking construction components/materials (Jang and Skibniewski 2008; Song et al. 2005; Torrent and Caldas 2009a). Apart from tracking of construction components, Pradhananga and Teizer (2013) demonstrated the potential of GPS to monitor equipment operation at an outdoor construction site. Lu et al. (2007) integrated GPS with dead reckoning of motion sensors to track vehicles in a construction site. This integration addressed the limitations of GPS when used in a highly dense environment that results in unreliable or unavailable GPS signals. Cheng et al. (2011) used a much more sophisticated sensing system, ultra-wideband (UWB), to track construction resources at a construction site.

Previous research has demonstrated significant progress in the tracking of construction resources in outdoor environments. In contrast, research in the domain of indoor tracking is not on par with the level of outdoor tracking. Many researchers (e.g., Hay and Harle 2009; Kjærgaard 2010; Park et al. 2013) highlighted that indoor environments are much more challenging for tracking than outdoor environments; the two environments are considerably different in nature and have different infrastructure and system requirements for tracking (Behzadan et al. 2008). The research domain of indoor tracking pertains to two of the three research objectives of this dissertation, which are covered in two chapters: CHAPTER 5 and CHAPTER 6.

1.4 Construction Safety

Construction sites need to be monitored continuously to detect unsafe conditions and take proactive actions to protect workers from potential injuries and fatal accidents. The monitoring of safety conditions of the workers is more challenging with increasing complexity of construction projects in recent years. Because of this trend in construction, safety managers are challenged with continuously monitoring and identifying incidents that may cause safety problems, and their abilities for this task and proper decision making in a timely manner may become inadequate in certain cases (Shahi et al. 2012).

Over the last decades, in monitoring and identifying safety-related occurrences, the construction industry, as discussed previously, heavily relied on ineffective manual methods. Because of a time gap between the occurrence of an event and its record, it further creates issues in collecting all necessary site data that potentially indicate the safety performance of workers. Such a method of data collection often neglects/ignores near-miss incidents because it is not recorded in real time and because associated workers suffer from many issues—fear, embarrassment, reputation, difficulty, peer pressure, lack of incentive, and lack of interest—which prevent them from reporting one.

Beyond the issues with reporting safety-related problems, the construction industry also faces a problem with recognizing/identifying potential safety problems—near-miss incidents are one of the significant cases (Jalaei and Jrade 2014; Kim et al. 2016b; Yang et al. 2015). The construction industry has not come to a consensus as to the interpretation of a near-miss event. According to the Occupational Safety and Health Administration (2016), a near-miss event is defined as "an incident where no property was damaged and no personal injury sustained, but where, given a slight shift in time or position, damage and/or injury easily could have occurred." The interpretation of this definition differs from person to person, depending on the subjective opinion of individuals, so subjective-decision making in regards to reporting of a near miss yields different conclusions. Because of this, many incidents that have potential to escalate to an accident are often not brought to attention of safety managers/engineers or associated personnel, so they are not properly recorded and treated for follow-up investigation and future analysis. These challenges hinder proper identification of frequent on-site safety issues. As such data/information is not available, our understanding of individual workers' safety performance and the overall safety performance of the project remains limited. The research domain of safety performance analysis pertains to one of the three research objectives of this dissertation, which is discussed in CHAPTER 7.

1.5 Research Needs/Knowledge Gaps

Despite much effort in the tracking/sensing and safety domains in construction, the construction industry is in urgent need of automated safety monitoring that allows continuous and reliable observation of construction site conditions. To establish the research goal and objectives for developing an automated system of safety performance monitoring and evaluation, research gaps are identified as follows:

1) Lack of reliable and effective personnel tracking methods in an indoor construction environment. Past research has not overcome one or more of the following:
    a. Ability to track at a complex, dynamic and large scale construction site
    b. Feasibility: impractical sensors, impractical deployment, cost, and scalability
    c. Impractical system and set-up manipulation
    d. Incorporation of tracking with construction resources such as Building Information Modeling (BIM) and safety hazard information
2) Lack of comprehensive methods for data collection for safety evaluation at an individual level
3) Lack of a formal method that analytically and computationally assesses the safety condition of individual workers with respect to on-site hazards
4) Lack of a framework that integrates all necessary processes (from site monitoring to analysis) for quantifying the safety performance of individual workers

CHAPTER 2. RESEARCH GOAL AND OBJECTIVES

2.1 Research Goal

The main goal of this dissertation is to develop a framework and methods for an automated safety performance evaluation system. The development of the framework and methods should address the research needs/knowledge gaps identified in the previous section. To achieve this, the following research questions need to be answers:

1) What needs to be considered and what approach can be used to overcome the limitations in indoor tracking?
2) How on-site tracking data can be integrated with a safety model to develop a formal procedure that quantitatively assess the safety performance of workers?

To answer these research questions, the dissertation consists of two research topics: the developments of tracking methodologies for data collection and the development of an analytical and computational procedure for evaluating the safety performance of workers at an individual level. The developed procedure targets to address safety problems that are difficult to be properly treated by conventional methods and thus require a more sophisticated and innovative technique, which is tracking.

The scope of this research includes zone-based hazards and workers' interaction with the hazards. According to the Health and Safety Executive (Health and Safety Executive 2015), over 20 percent of fatal accidents in the construction industry are associated with workers moving through a construction site. In fact, accidents also occur to workers while they are executing their tasks. However, because their direct causes of such accidents are various, which require unique handling methods for each cause, the scope is limited to zone-based hazards that can create dangerous situations to workers. The zone-based hazards include, but are not limited to, hazards associated with physical condition of a construction site, which accounts for 38% of incident cases (Awolusi and Marks 2016). Such hazards are represented by their spatial and temporal relationship and the type of construction activities, if any is nearby. The scope does not include hazardous events that occur to workers while they are working (e.g., cutting fingers, falling from a ladder, equipment operation mistakes, electrocution, etc.).

2.2 Research Objectives and Scopes

To achieve the research goal, three research objectives related to data collection and safety evaluation are identified as follows.

- The first objective, which is discussed in CHAPTER 5, is to create a methodology for tracking that targets a noisy, complex indoor construction environment
- The second objective, which is discussed in CHAPTER 6, is to develop a hybrid-tracking approach that integrate Bluetooth low-energy (BLE) sensors, motion sensors, and BIM
- The third objective, which is discussed in CHAPTER 7, is to develop a computational and analytical procedure that uses an input of tracking data of workers to assess the safety condition of workers. The third objective involves zone-based safety issues that the tracking information can be used to assist in safety performance assessment.

2.2.1 Objective 1: Absolute Tracking

The first of objective of this research is to create a method for tracking that can overcome the fragility and unreliability of received signal strength indication (RSSI) at a noisy, complex indoor construction environment. The development of this research is two-fold: 1) to investigate RSSI and find a probability distribution model that can best represent the behavior of RSSI and 2) to develop and assess a probabilistic local search (PLS) algorithm that uses the acquired probability distribution model.

The scope of analysis is limited to testing the accuracy of the developed algorithm. The analysis measures the performance of the system by comparing two commonly used distance-based algorithms, trilateration and MLE. To test the performance of the proposed algorithm under various levels of signal interference, this study uses computer simulation of signals. The major purpose of using this computer simulation is to create, without excessive human effort, a multitude of scenarios with different levels of error in distance measurement, which emulate signal interference that is expected from a complex, dynamic construction site. The computer simulation is particularly selected based on an assumption that the dynamic and complex nature of an indoor construction site as well as various interactions among workers, equipment and materials create various levels of signal interference. In generating signals, the computer simulation is based on signal data sets that have been collected at a particular indoor construction site; this allows the generation of computer-simulated noisy signals to reflect the characteristics of signals expected from other indoor construction sites.

2.2.2 Objective 2: Hybrid Tracking

The second objective of this research is to create and evaluate a hybrid-tracking approach using a knowledge-based framework that incorporates BLE sensors, motion sensors and BIM. The first component, BLE sensors provide absolute position information but are prone to fluctuation resulting from high levels of noise; the second component, motion sensors provide relative position information but are vulnerable to drift; and the third component, building geometric data provide cognitive reasoning of a target's movement that is used to improve the tracking accuracy. This knowledge—characteristics of the three components—is particularly used in the development of an integrated, probabilistic framework that uses their advantages to overcome the limitation of the other components.

The advancement of this development beyond the BLE tracking system, which is discussed in CHAPTER 5, is the improved tracking performance through the system integration. Accordingly, the scope of CHAPTER 6 is to test the hypothesis whether the knowledge-based hybrid tracking system can correct errors developed in each of the system components and thus increase the accuracy of tracking. The scope of the study includes the development of the knowledge-based hybrid tracking system, a full-scale field experiment at an indoor construction site, and the subsequent analysis and discussion to prove the hypothesis.

2.2.3 Objective 3: Worker Safety Assessment

The third objective of this research is to model a zone-based safety risk (ZBSR) of individual workers by using real-time location data from the developed tracking system. The ZBSR model aims to mathematically process the real-time data to generate measures that can assist in understanding of workers' behaviors. The behaviors of workers are represented by their safety performance indices that are computed based on their locational information with respect to identified hazards, associated parameters, such as exposure level, exposure frequency, and potential degree of injury/damage. In the development of this safety evaluation procedure, this research integrates the developed tracking module with the ZBSR model. This procedure serves as an objective method of safety performance evaluation that is determined by data collected onsite.

The scope of this research includes zone-based hazards and workers' interaction with the hazards. According to the Health and Safety Executive (Health and Safety Executive 2015), over 20 percent of fatal accidents in the construction industry are associated with workers moving through a construction site. In fact, accidents also occur to workers while they are executing their tasks. However, because their direct causes of such accidents are varied, which require unique handling methods for each cause, the scope is limited to zone-based hazards that can create dangerous situations to workers. The zone-based hazards include, but are not limited to, hazards associated with physical condition of a construction site, which accounts for 38% of incident cases (Awolusi and Marks 2016). Such hazards are represented by their spatial and temporal relationship and the type of construction activities, if any is nearby. The scope does not include hazardous events that occur to workers while they are working (e.g., cutting fingers, falling from a ladder, equipment operation mistakes, and electrocution).

CHAPTER 3. LITERATURE REVIEW

This chapter presents a thorough review of previous research associated with the identified research topics: 1) tracking and 2) safety monitoring and evaluation. Based on the literature review, three specific research objectives, which are individually addressed in CHAPTER 5, CHAPTER 6, and CHAPTER 7, are identified for the research topics.

3.1 Tracking in Construction

3.1.1 Various Tracking Technologies

The introduction of GPS initiated exploration of asset tracking in outdoor construction environments (Leung et al. 2008; Lu et al. 2007; Park et al. 2011; Torrent and Caldas 2009b). Despite the capability of GPS in outdoor tracking, GPS faces a considerable drawback for tracking a target in an indoor environment because of the inability of satellite signals to penetrate through building materials. The development of construction applications with GPS triggered the use of other sensing technologies (e.g., Radio Frequency Identification, video camera, laser scanning, ultra-wideband, Wi-Fi). As a result, researchers (Cho et al. 2014; Gong and Caldas 2011) have explored outdoors by using a video camera system and a laser scanning system. These systems have demonstrated their performance in certain cases of outdoor applications, but they suffer from certain issues when applied to a complex site in real time; A video camera system suffers from a limited field of view and difficulty in deploying the system over a complex site; a laser scanning system necessitates significant infrastructure as well as considerable time for handling/processing scanned image/point cloud data, which makes such systems not suitable for use in a fast changing indoor construction site.

Another promising sensing technology, named UWB, received significant attention from many researchers (Carbonari et al. 2011; Cho et al. 2010; Khoury and Kamat 2009; Park et al. 2016b), leading to a number of research studies. As of yet, state-of-the-art research has not overcome certain practical limitations of this technology that impede its widespread application in the construction industry; UWB is not cost-effective and requires line-of-sight, time-consuming system coordination, complex deployment of sensors, and network configuration (Cho et al. 2010; Khoury and Kamat 2009; Torrent and Caldas 2009b).

Despite the previous research efforts, tracking in indoor environments still remains incomplete because of many challenges. Part of these challenges appear in the form of signal interference such as signal degradation, occlusions, obstructions and multipath effects, which negatively affect the quality of signal (Lee et al. 2012; Luo et al. 2011). Unfortunately, construction sites tend to be large, complex, scattered, and dynamic, which intensifies the identified challenges for reliable tracking. Researchers investigated many indoor tracking solutions using various technologies and methodological approaches. However, each of the indoor tracking solutions is limited by its own unique shortcomings and also a trade-off among accuracy, real-time capability, cost, scalability, adaptability, hardware and software requirement, system complexity, and many others (Palumbo et al. 2015). To mitigate these practical limitations, this study adopts BLE, which offers small form factor, low cost, low energy consumption, ease of use, and flexibility.

3.1.2 RSSI-based Indoor Tracking

This sub-section presents a thorough review of state-of-the-art research focusing on RSSI-based tracking technologies, which is the communication protocol of the BLE technology. Through this review, the study finds a research gap and derive a research need for investigating a more fundamental level of algorithmic study, which is specifically addressed and discussed in CHAPTER 5.

The benefits of RSSI-based tracking systems triggered extensive research in sensing and tracking targeting construction applications. In the context of indoor tracking, investigators have explored various experimental and algorithmic studies by using RSSI-based sensors to obtain accurate location data of construction assets. Kotanen et al. (2003) conducted an experimental study with conventional Bluetooth technology, which showed an accuracy of 3.76 meters. Although they used an advanced algorithm, Kalman Filter, their experiment was limited to static data measurements, which still need to demonstrate its capability for tracking a moving object. Another limitation of their study was an unrealistic set-up that was designed for the tests (e.g., removal of all furnishings that may interfere with signals). Another study performed by Luo et al. (2011) also presents similar problems for testing their systems as to eliminating potential signal reflection and multi-path effects. Such findings would not equally be applicable in a realistic situation in which signal interference adversely affect the signal communication of sensors; because construction sites tend suffer from these issues more frequently than other environments, validation of a system in a realistic situation is crucial. Fang et al. (2016) recently conducted an on-site tracking study by using a cell-based RFID proximity locating method. Their study is one of few studies that actually implemented an experiment at a large-scale construction site; many sensing technologies introduced by other researchers are impractical to cover a large and complex area. Despite their application to a large construction site, such a type of system/method is unable to pinpoint the location of the target and may not be suitable for complex, dynamic environments due to highly increased complexity in the design of system layout and the size of required infrastructure.

In other aspects of research, researchers investigated various algorithmic methodologies using various sensors. For example, Montaser and Moselhi (2014) used RFID in comparing localization algorithms, which are triangulation and proximity, and demonstrated a cost-effective solution with 1 - 3 meters accuracy. However, their deployment plan is not generically applicable because of their site-specific system configuration with room-based sensor deployment. Li et al. (2014) developed an iterative maximum likelihood estimation (MLE) that includes the effect of RSSI attenuation by simultaneously using certain BIM elements. Their contribution pertains to proposing a method that handles part of the negative effects of signal interference from existing walls. Although the method was an innovative, integrated solution, it is limited to use only walls and requires a BIM model to execute the interactive MLE process. Algorithmic studies (Chai et al. 2017; Zhuang et al. 2016) have also been conducted by exploring a combination of support vector regression/fingerprinting and Kalman filtering to achieve improved tracking. However, these systems may face practical issues in evolving construction sites.

Many practical problems that prevent the use of tracking systems in construction sites stem from lack of understanding of the challenges. Lee et al. (2012) and Luo et al. (2011) discussed the potential issues resulting from signal interference such as signal degradation, occlusions, obstructions and multi-path effects. Researchers (Elnahrawy et al. 2004; Lymberopoulos et al. 2006; Skibniewski et al. 2007) explicitly discussed inherent RSSI problems that limit the accuracy of RSSI-based tracking systems especially when they are used in a complex indoor environment. Despite the past research efforts have explored tracking in various aspects, the aforementioned challenges caused by a complex, dynamic indoor construction environment has received little attention.

In sum, a great deal of uncertainty about the behavior of RSSI at a complex indoor construction site and its impact to tracking remains unknown. Whereas numerous studies have studied tracking methodologies, to the best of the author's knowledge, no study has adequately covered this topic. CHAPTER 5 aims to reduce the gap in knowledge in the RSSI-based tracking system when it is used in a noisy environment like dynamic, complex construction environments. CHAPTER 5 investigates the behavior of RSSI signals at a more fundamental level and then develops a probabilistic localization algorithm for minimizing the negative impacts of signal interference resulting from a multitude of interactions among workers, equipment, and materials.

3.2 Integrated Tracking in Construction

3.2.1 Needs for More Advanced Tracking Approaches

Previous research has mainly focused on the development of tracking systems by using various technologies. Although researchers have made significant progress over the last decade, indoor tracking in construction sites encounters many challenges and the previous research efforts, which have not overcome all of these challenges, are still limited. The nature of complex indoor construction sites in combinations of many confined, congested spaces causes difficulty in tracking from both hardware and algorithmic perspectives. In discussion of the hardware aspects, scalability and deployment issues are often found because of many unique spaces and high volume of traffic from construction assets (Liu et al. 2007; Skibniewski and Jang 2009). Also, the form factor and complex set-up of tracking systems make them not suitable to be used in a consistently evolving construction site as the site requires frequent relocation of sensors. Other problems include signal unreliability, interference, measurement accuracy, and cost.

In discussion of the algorithmic perspective, researchers have explored machine-learning algorithms such as the K-nearest neighborhood (K-NN) algorithm (Dawes and Chin 2011; Widyawan et al. 2007). However, such learning-based algorithms present significant drawbacks when applied to an environment that is changing. Construction sites are rapidly evolving, and the learned data used in such algorithms may not be applicable especially after considerable changes occur in the environment. Other researchers (Li et al. 2014b; Subhan et al. 2013; Taneja et al. 2010) explored algorithmic studies to mitigate the problems caused by unreliable signals, but their approaches are still limited with unique problems (e.g., fluctuating estimation and working in certain settings).

To overcome the limitations in these two aspects, recent research has studied hybrid-tracking solutions by combining multiple sensors/systems; hybrid/integrated tracking solutions are discussed in detail in the following sub-section. While such solutions have been examined by many researchers, very few researchers has investigated methods that dynamically incorporate prior knowledge of the behaviors of multiple sensors in an integrated tracking system. This indicates a strong need for investigating/exploring a more knowledge-intensive tracking system, which is the major objective of CHAPTER 6.

3.2.2 Hybrid-Tracking Approaches

Integrated tracking systems that use multiple sensors/data have shown the ability to take into account discrepancies in sensor data and thus reduce error in position estimation. One of the tracking research topics that researchers have attempted in their hybrid approaches is motion sensors. Taneja et al. (2016a; b) proposed methods to generate a navigation model from BIM and used tracking sensors with a map-matching model to evaluate the performance of the sensors in tracking. They presented an innovative method, but their approach still suffer from a few challenges, such as a trap and drift from the IMU sensor and inconsistent performance from the Wi-Fi sensor. Visual markers and IMU sensors are used by Neges et al. (2014) for improved indoor navigation system. While this method offers practical potential in certain cases, it is not designed for construction applications and their system set-up is limited to be used at a busy, complex on-going construction site. Park et al. (2016b) developed an integrated system with wheel encoders, motion sensors, UWB sensors and a digital compass for an autonomous navigating system. Although they showed an effective way to link multiple data types, the main basis of the system is wheel encoders, which are effective in navigating but not in general asset tracking. In addition, their system did not resolve the major drawback of IMU, which is drift.

To compensate for the issues with drift in IMU, researchers developed methods that impose constrains on position estimates through additional information, such as alternative sensor data and geometric information. Camera images are used to extract a line detection routine for correcting drift in gyroscope data (Jiang et al. 2004). However, because this system primarily targeted outdoor environments and may not perform comparably in a cluttered indoor environment. Also, researchers investigated approaches that use certain constraints to reduce the drift error; Li et al. (2012) used corridor and wall boundaries as a source of constraints to assist the computation of relative movement from IMU, and Park et al. (2016c) used BIM data—similar geometric constraints—to assist BLE-based tracking. These studies have shown potential to diminish the adverse effect of error accumulation in motion sensors, but their approaches rely on a single type sensor, which is difficult to eliminate the shortcomings of motion sensors.

Previous studies have reported another common challenge in RSSI-based tracking technology, which is the unreliability of RSSI measurements. Over the last decade, a number of researchers have sought to integrate multiple systems for handling this problem. In one study (Li et al. 2014a), the authors integrated BIM and a RF-based sensing system for localization in emergency response operations. Similarly, Jang and Skibniewski (2008) combined a Zigbee-based system with ultrasound to minimize the multipath effect and thus enhance the accuracy of positioning. However, their system suffers line-of-sight issues and has been mainly tested in an outdoor environment.

Despite these previous research studies with integrated and algorithmic approaches, they have not sufficiently investigated systems with respect to the interaction of system components. Table 1 shows a summary of a methodological review of recent research studies. As shown in this table, researchers have mainly focused on improving accuracy of tracking through system integration and/or the development of combined algorithmic approaches. As of yet, very little attention have been placed on the study of error correction of sensor data itself through system integration. CHAPTER 6 creates a hybrid-tracking approach that uses a knowledge-based framework. Under this framework, the chapter presents a probabilistic error correction mechanism to improve tracking.

Table 1. A summary of methodologies in recent research

Method	(Fang et al. 2016)	(Kim et al. 2016b)	(Park et al. 2016b)	(Li et al. 2015)	(Faragher and Harle 2014)	(Li et al. 2014a)	(Taneja et al. 2016b)	(Li et al. 2012)	(Zhuang et al. 2016)	(Chai et al. 2017)	Proposed Approach
Absolute positioning	O	O	O	O	O	O	X	X	O	O	O
Relative positioning	X	X	O	X	X	X	X	O	X	X	O
BIM for tracking	Δ	Δ	Δ	Δ	X	O	O	X	X	X	O
Error correction through integration	X	X	X	X	X	O	X	X	X	O	O

Δ: BIM is used for visualization or path display

3.3 Safety Monitoring/Assessment in Construction

Over the last decade, researchers have explored various technologies and methodologies to enhance safety of workers at construction sites. However, site/safety managers often find difficulty in performing such safety inspection because of complex environment of construction sites and continuous changes in daily activities. Insufficiently identified safety issues lead to potentially hazardous events that may escalate to injuries and fatal accidents. Although the construction industry has adopted various safety trainings and regulations to enhance workers' safety, such safety issues have threatened workers' health and lives and become a significant problem.

3.3.1 Current Practices for Safety Monitoring

Continuous monitoring of a construction site is crucial to provide workers with a work friendly environment that presents minimal hazards for their health and safety. As an effort for enhancing safety, the construction industry has employed several methods, such as accident investigation, self-inspection, survey, and job hazard analysis. However, these are passive forms of observation/method of data collection. Because they require site observation or they are created after the occurrence of undesired events, all incidents that have the potential to lead to accidents that may not necessarily be captured.

For certain tasks, OSHA requires the designation of a competent person for safety purposes; a competent person is "one who is capable of identifying existing and predictable hazards in the surroundings or working conditions which are unsanitary, hazardous, or dangerous to employees, and who has authorization to take prompt corrective measures to eliminate them" (OSHA 2016). The monitoring of safety conditions of the workers is more challenging with increasing complexity of construction projects in recent years. Because of this trend in construction, the safety managers are challenged with the task of continuously monitoring and identifying incidents that may cause safety problems, and their abilities for this task and proper decision making in a timely manner may become inadequate in certain cases (Shahi et al. 2012). Furthermore, the limited capability of safety/site managers causes difficulty in ubiquitous and continuous monitoring of the construction site for thorough identification of safety issues (Jalaei and Jrade 2014; Kim et al. 2016b; Yang et al. 2015).

As a result, near-miss events are often ignored/neglected by associated personnel without being properly recorded (Yang et al. 2014). A study (Li et al. 2016) pointed out that the number of near-miss incidents are considerably more than the number of actual recorded accidents. Unfortunately, all near-miss incidents possess the potential to escalate to accidents, resulting in significant damage to not only the associated person but also the associated contractors. Despite the efforts in promoting a safe construction environment, construction safety practices are still inadequate, and the industry still lacks such an important measure for handling safety incidents.

3.3.2 Advanced Methods for Safety Monitoring

As discussed previously, the promise that information and sensing technologies offer has drew significant attention from researchers, and many sensing technologies have been studied for construction applications. Pradhananga (2014) explored an outdoor proximity application to develop a method for quantifying safety incidents for human and equipment interactions. To the best of the author’s knowledge, this work is the most related research that attempted to use tracking technology for quantifying safety-related issues. However, his research work shows significant differences from the work presented in this dissertation in many aspects including "indoor vs. outdoor", "probabilistic approach vs. deterministic approach", "use of a commercial product vs. use of a developed tracking system (to overcome the limitations of existing limitations)", and "different factors in quantifying the safety performance."

Focusing on the indoor research domain, previous research focused on the ability of such technologies in autonomously monitoring a construction site by using a tracking methodology. Table 2 summarizes recent research, conducted since 2010, that is closely related to indoor tracking and safety for construction. The table analyzes each research study with respect to 1) indoor tracking capability, 2) test location, 3) resolution to safety, 4) primary objective, 5) type of technology, and 6) use of BIM source. Even after decades of research in the tracking domain, many of these recent studies for indoor tracking shown in Table 2 still focus on acquiring a reliable and accurate tracking system/method.

Table 2. Summary of recent research for indoor tracking and safety

	(Cho et al. 2010)	(Wu et al. 2010)	(Woo et al. 2011)	(Carbonari et al. 2011)	(Shahi et al. 2012)	(Lee et al. 2012)	(Soleimanifar et al. 2014)	(Costin and Teizer 2015)	(Li et al. 2016)	(Shen and Marks 2016)	(Fang et al. 2016)	(Kim et al. 2016b)	Proposed Approach
Indoor tracking	O	Δ	Δ	O	O	O	O	O	Δ 3*	X	Δ 3*	O	O
Construction site	O	X	O	O1*	O	X	Δ	X	O	O	O	O	O
Safety	X	O	X	O	X	X	X	X	O	O	X	O	O
Objective	A	S	A	OH	A	A	A	A	S	S	A	S	S
Technology	U	Ul	W	U	U	R	R2*	R	BLE	NA	R	R	BLE
BIM	X	X	X	X	X	X	X	O	X	O	O	O	O

1*: small site testing
2*: radio signal-based technology (not specifically mentioned as to what technology)
3*: proximity range detection-based tracking
Objective: Accuracy(A), Safety(S), Overhead Hazard(OH)
Technology: UWB(U), Ultrasonic(Ul), Wi-Fi(W), RFID(R), Bluetooth Low Energy(BLE)

Until now, minimal research has been conducted in practical safety application development by using tracking. Only few research studies (e.g., (Kim et al. 2016b; Li et al. 2016) addressed safety issues using an indoor tracking methodology, but they are yet limited in some aspects. Although Kim et al. (2016) attempted to use tracking information to identify on-site hazards, the methodology that uses deviation of optimal routes in identifying the occurrence of a hazard is unrealistic and specific to limited situations. The other study (Li et al. 2016) offered a new method for quantifying on-site hazard conditions by using tracking information. However, this study is also limited in the following aspects: 1) the tracking technique seems to rely on proximity range detection method, which only detects a target in an on-and-off manner (e.g., enter an area or exit an area), 2) the method requires historical records, which is one of their weaknesses to overcome in their future research. Note that there exists other safety research using sensing technologies, which use methodologies different from a localization methodology, but such research is excluded.

Continuous monitoring and collecting a data stream from the construction site is indubitably important for detecting unsafe conditions/hazardous events and eliminating the potential to escalate the accidents. Despite this, as of yet, little research has explored the issue of construction safety by using real-time location systems (RTLSs), and researchers have not yet developed a holistic, integral approach. To address this, CHAPTER 7 develops a computation and analytical model that uses on-site tracking data as an input to evaluate the safety performance of workers onsite.

CHAPTER 4. RESEARCH FRAMEWORK

This chapter presents the methodological framework for and system architecture of the automated safety performance evaluation system. To facilitate the implementation of the automated safety performance evaluation system, a methodological framework is proposed as shown in Figure 2. This framework consists of five layers for each of the modules that describe sequential steps of the module implementation. The first three steps are independently performed for each module as the two modules play a unique role in the automated safety performance evaluation system. Then, the tracking results are integrated into the safety module in the next step of analyzing the safety condition of workers with respect to nearby hazards. After the evaluation of the safety condition, the system generates an output in the form of an index that quantitatively describes the safety performance of workers.

	Tracking system	**Safety system**
Set-up	Sensor Deployment	On-site Hazard Identification
Data	Sensor Data Collection	Hazard Modeling and Registration
Processing	Algorithms and Data Fusion	Detect Associated Hazards
Analysis	Safety Condition Evaluation by Combining the Tracking and Safety Modules	
Output	Safety Performance Index	

Automated Safety Performance Evaluation

Figure 2: Methodological framework

Given the framework, this research develops a system architecture by discretizing the work into independent modules (research objectives). Figure 3 presents detailed algorithmic and systematic implementations of each module as well as the integration of the modules into a single platform that performs automated safety performance evaluation of workers. This integration fulfils the last step of evaluating the safety performance of individual workers based on their location data collected by the tracking system. The following chapters sequentially discuss the development of each research objective.

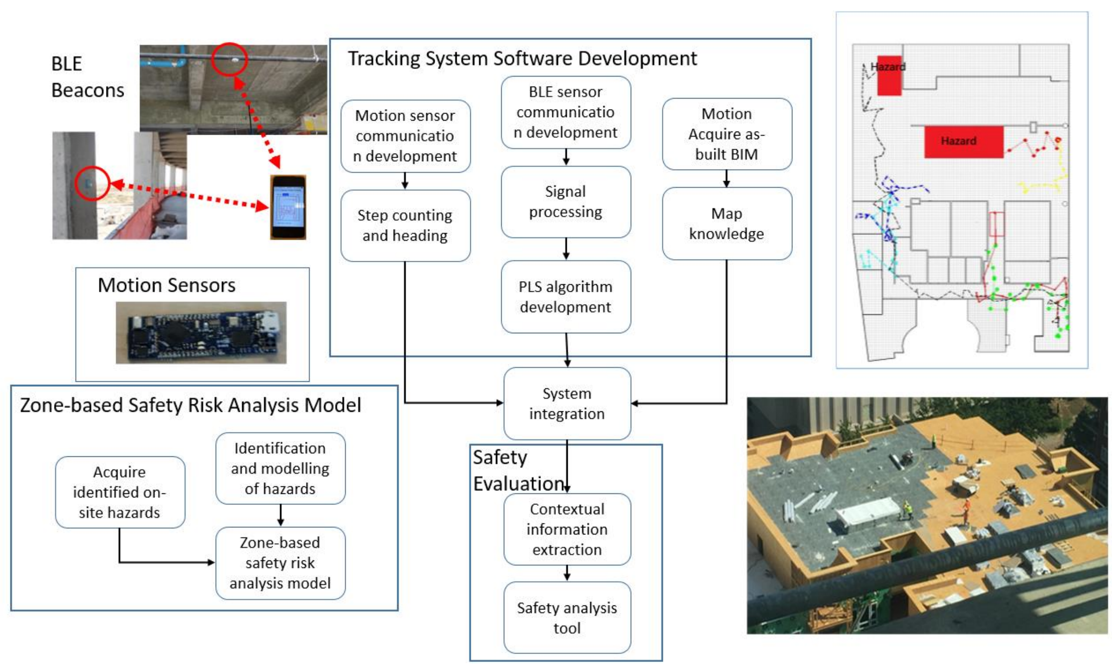


Figure 3: System architecture

CHAPTER 5. A BLE-BASED ABSOLUTE TRACKING APPROACH

This chapter develops the PLS algorithm in five steps in two categories as follows:

- Investigation and probabilistic modeling of RSSI
  - Signal processing
  - Investigating the behavior of RSSI
  - Seeking a probability distribution model for RSSI
- Creating of PLS
  - Developing PLS in conjunction with the probability distribution model
  - Assessing PLS through a numerical simulation approach

Each of these steps are discussed in the following sections.

5.1 Signal Processing

This sub-chapter pertains to the basic development of signal communication of the BLE-based tracking system through signal processing. In Bluetooth signal communication, RSSI is used as a measurement of the signal power in transmitted radio signal. Raw RSSI, when it is first received, tends to be noisy, and it is known to operate in a high level of fluctuation. Although this characteristic of RSSI depends on the set-up of devices, the capabilities of the devices, and the environmental condition in which the BLE systems operate, it is a general phenomenon in radio signal communication. To alleviate the adverse effects from noisy data, this study first uses a signal processing approach. By processing received signals, the system removes unwanted elements of the received signals and/or reduces the influence of such elements, and intensify certain signals. This manipulation allows the system to operate with certain sets of received signals that are transformed to be more insightful and/or more interpretable. Such transformed data are better off in delivering the hidden state of the environmental condition that the raw signals attempt to capture.

The signal processing approach in the proposed BLE-based system uses two steps: 1) reliability check and 2) adaptive moving average. First, the reliability checking method checks whether a newly received datum point has experienced significant degradation through various sources of signal interference and whether the newly received datum point presents a strong significance to the data set. Second, after the reliability check, the system proceeds with the adaptive moving average filter. This filter is a modified/improved version of a moving average filter, which is shown in Equation 1.

Based on the results of the reliability check, the system determines the weight, α, for the moving-average equation in three different ways in a broad manner, which is described in Figure 4. If the new datum point is found unreliable, the weight, α, is increased; if the new datum point is found to be strongly significant, the weight, α, is reduced; otherwise, the weight, α, remains the same. The changes in the weight, α, is to adaptively reflect the significance of the new data to the overall averaged result. The reduction of the weight, α, is to increase the contribution of a new datum point to the overall averaged result while the amplification of the weight, α, is to reduce the contribution of a new datum point to the overall averaged result. To provide a visual illustration of how these methods are different, 500 RSSI data are collected at a constant distance. Figure 5 shows comparison of raw data, data that are processed by a moving average filter with the weight, α, of 0.8, and data that are processed by the proposed adaptive moving average filter with the weight, α, of 0.8. Compared with the result of the moving average filter, that of the adaptive moving average filter is smoother, that is, it shows less degree of fluctuation, while maintaining the overall trend of the raw data. This provides strong evidence that the proposed method more effectively manipulates noisy signals, so the following development of the research takes advantage of the method.

$$y[n] = x[n] \times \alpha + y[n-1] \times (1-\alpha) \tag{1}$$

```
• Pseudo Code for Adaptive Signal Processing

//aveRSSI: averaged RSSI or processed RSSI
checkDifferenceRSSI = rawRSSI – aveRSSI;
weight1 = assigned some value;
weight2 = this needs to be 1 – weight1;
// threshold = [threshold1, threshold2]
// alpha = an adaptive factor
If (checkDifferenceRSSI >= threshold1 && checkDifferenceRSSI < threshold2) {
        weight1 = weight1;
Else if (checkDifferenceRSSI >= threshold2) {
        weight1 = weight1 + alpha;
Else if (checkDifferenceRSSI <= threshold1) {
        weight1 =  weight1 - alpha;
}
Weight2 = 1 – weight1;
aveRSSI = rawRSSI*weight1 + aveRSSI*weight2;
```

Figure 4: Pseudo code for the adaptive signal processing

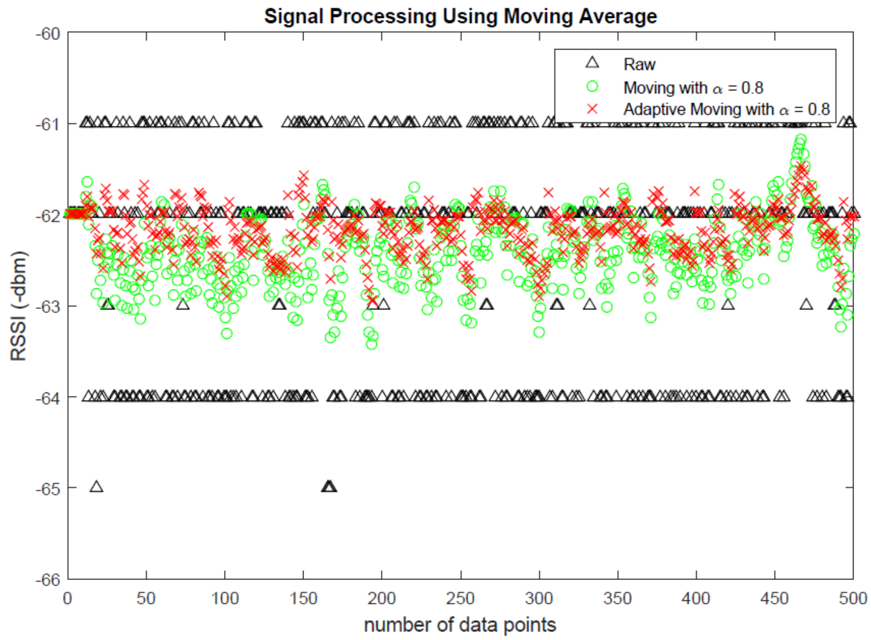


Figure 5: Adaptive moving average filter

5.2 Investigation of RSSI

As discussed in the literature review section, previous research has not sufficiently examined the challenges posed by a complex indoor environment through various forms of signal interference. This sub-chapter studies RSSI to understand its behavior at a more fundamental level. Experimental data collection is carried out to present the basis of the signal behavior for discussion and analysis. Figure 6 shows the testbed and test path for this data collection. The two-dimensional (2D) floor plan in Figure 6 also displays the identifications of BLE sensors and their coordination next to each of the x marks.

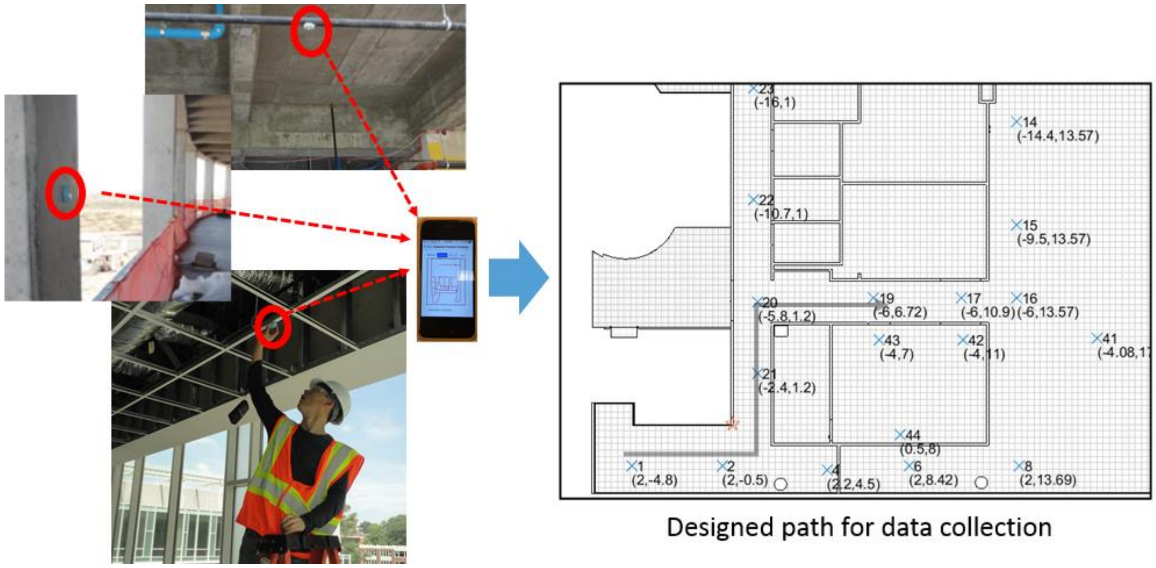


Figure 6: BLE sensor deployment, site testbed, and test path

The collected data are plotted in Figure 7. To describe the varying behavior of the signal, boxes and ovals that cover certain ranges of the signal are drawn in each of the two sensors in Figure 7. The ranges of signals indicated by the rectangular boxes, compared with those indicated by the ovals, appear to be smaller as the degree of their fluctuation is smaller. The smaller range implies that certain sensors can be more reliable than other sensors at a particular time. Another important observation is that the fluctuation level changes as the subject moves to different locations. That is, the level of fluctuation in a particular sensor changes, depending on the location of the subject. This is clear evidence that the quality of signals from a sensor varies with the location of the subject.

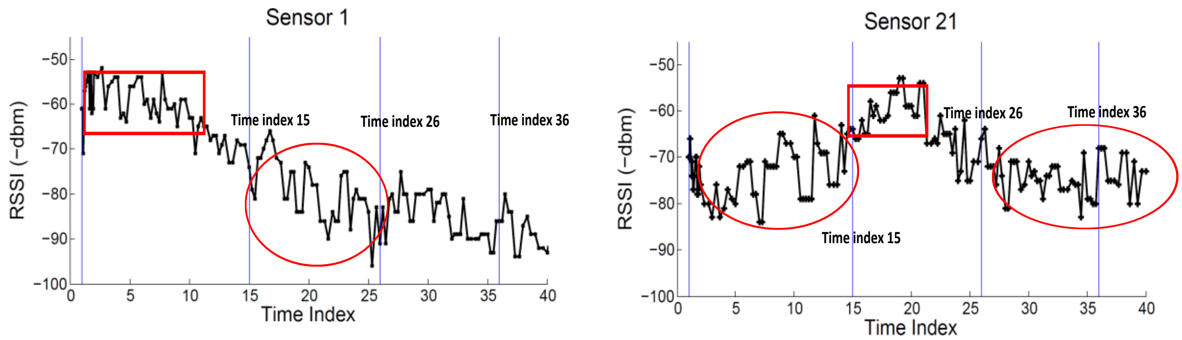


Figure 7: Measured signals during the course of test movement

Figure 8 shows RSSI variation and its projection to distance. This conversion is based on a well-known signal propagation relationship between RSSI and distance as shown in Equation 2 (Chintalapudi et al. 2010; Li et al. 2005). It is observed that the distance converted from the larger range of signals is spread over a much larger distance range than that converted from the smaller range of signals. This reveals a significant finding on the RSSI behavior that the conversion of the RSSI to distance increasingly signifies the effect of signal fluctuation. In sum, the investigation of RSSI unveils an important observation that measured signals are unequally reliable; some are more reliable or less reliable than other. This finding forms the foundation of the PLS algorithm, which will be developed later in this chapter.

$$Distance = 10^{\left(-\frac{abs(RSSI_1)+RSSI}{10n}\right)} \quad (2)$$

$RSSI_1$: RSSI measured at 1 meter
n: path loss constant

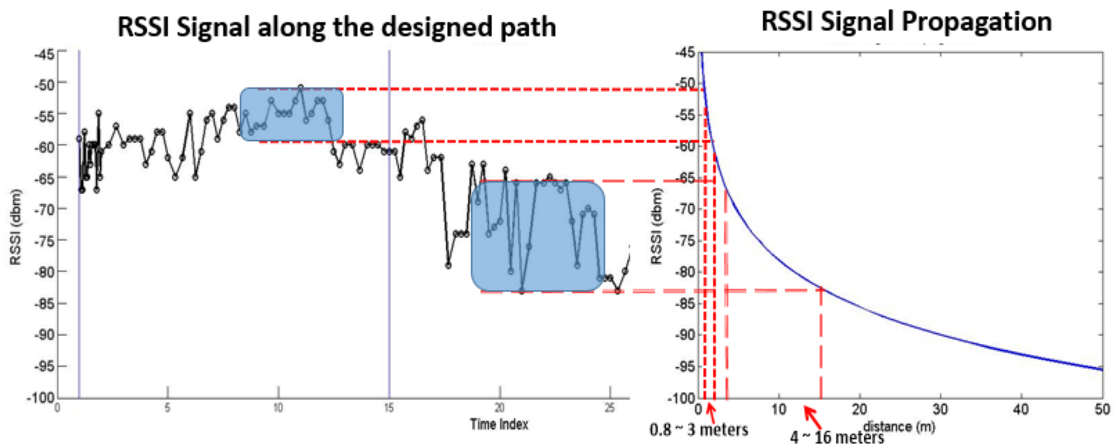


Figure 8: RSSI variation and its projection to distance

5.3 Probabilistic Model of RSSI for the BLE-based Tracking System

Through the experimental investigation of RSSI signals, this research has found evidence that the communication between a transmitter and a receiver is inconsistent especially when they are applied in a complex, indoor environment. In other word, signals received by a mobile device, regardless of signals sent by a transmitter, have various levels of reliability. This sub-section seeks to find a probability distribution model that can represent RSSI through another experimental data collection and follow-up analysis with data fitting. The probability distribution model found from this data fitting enables a quantitative evaluation of received signals that become inputs of the localization algorithm developed in the next section.

5.3.1 Data Modelling

Several sets of RSSI data collected at various distances. To find a probability distribution model for RSSI that is reliable, data are collected while maintaining a light of sight condition between the transmitter and receiver. For description purpose, the following analysis includes certain experimental distances, 1 m and 3 m, each of which is composed of approximately 600 to 1,000 data points. During the data collection, the data have been processed by the signal processing method. An optimal set-up for the BLE sensors is used with a power level of -4 Decibel-milliwatts (dBm) and an advertising interval of 100 milliseconds (ms).

Figure 9 shows the four histograms of the collected RSSI signals; the x- and y-axis indicate the measured RSSI values and the observed frequencies, respectively. The histograms are visually analyzed to assist in the selection from a variety of probability distribution models. It is apparent from the histograms that both data sets have approximately normally distributed shapes, and that the 3 m data set has a larger variation than that of the 1 m data set. To further verify the correctness of this visual inspection, a more rigorous mathematical analysis, data fitting, follows.

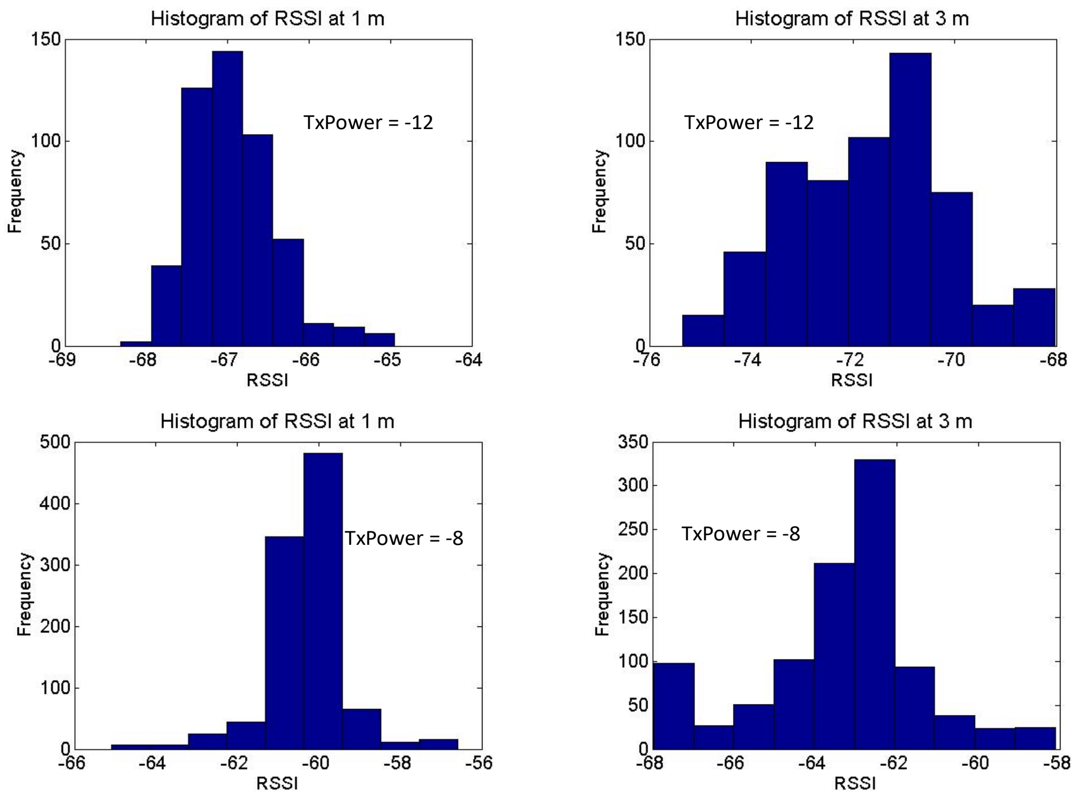
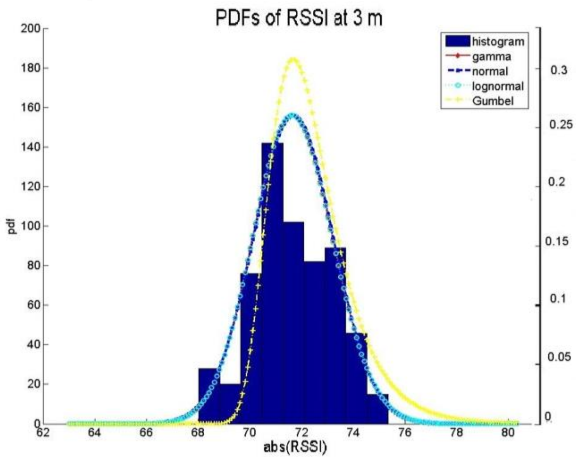


Figure 9: Histogram plot of RSSI

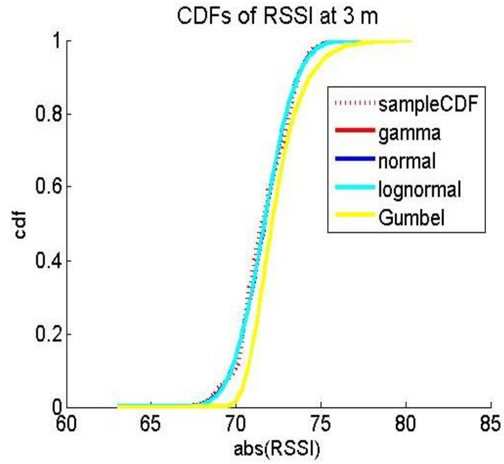
5.3.2 Data Fitting

This section discusses quantitative analysis of four trial distributions through parameter estimation and goodness of fit tests. The four distribution models are as follows: 1) normal, 2) log-normal, 3) gamma, and 4) Gumbel distributions. Equations 3 to 6 show their formulae. In the function notation, the parameter x is the absolute value of RSSI, and other parameters followed by a semi-colon are the parameters, which are estimated for data fitting. The parameters for each of the distributions are estimated from the collected data set. Then, the probability density function (PDF) and cumulative distribution function (CDF) of the trial distributions are plotted and compared in Figure 10. Based on these plots, it is concluded that the Gumbel distribution is unfitting to the experimental data set, so it the distribution is excluded for the selection of the distribution model.

Normal distribution	$f(x;\mu,\sigma)=\frac{1}{\sqrt{2\sigma^2\pi}}e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}$	(3)
Gamma distribution	$f(x;\mathrm{k},\lambda)=\frac{\lambda(\lambda x)^{\mathrm{k}-1}e^{-\lambda x}}{(k-1)!}, for\ x>0$	(4)
LogNormal distribution	$f\left(x;\mu_{\ln_X},\sigma_{\ln_X}\right)=\frac{1}{x\sigma_{\ln_X}\sqrt{2\pi}}e^{\left[-\frac{1}{2}\left(\frac{\ln x-\mu_{\ln_X}}{\sigma_{\ln_X}}\right)^2\right]}, for\ x>0$	(5)
Gumbel distribution	$f(x;\alpha,u)=\alpha\ e\left(-\alpha(x-u)-e^{-\alpha(x-u)}\right)$	(6)



a) PDF comparison



b) CDF comparison

Figure 10: PDF and CDF plots of RSSI

Additionally, a Chi-square goodness of fit is carried out to evaluate and compare the three remaining distributions. Table 3 summarizes the results of this analysis; the lower value implies that the corresponding model fits better to the experimental data set. The goodness of fit analysis reveals that the best prediction model, for all test cases, alternates between the normal distribution and the log-normal distribution. Overall, the results of these experiments and analyses suggest that a normal distribution follows RSSI well, so it is used to model RSSI. This probability model and the finding about the trend of variation form the basis of the PLS algorithm as to how the probability model is applied to a position estimation of a target.

Table 3. Chi-square goodness of fit test

Test	Normal distribution	Gamma distribution	Log-normal distribution
1	52	47	45
2	54.3	54.3	54.4
3	103	97	94
4	247	244	243
5	158	151	147
6	119	128	133
7	108	115	120
8	93	99	101

5.4 Probabilistic Local Search Tracking Algorithm for BLE Tracking

This sub-section discusses the development of the PLS algorithm, which is specifically designed to cope with the adverse signal interference from a complex indoor construction environment. This algorithm aims to distinguish reliable and unreliable signals by applying a normal distribution probability model to each of the received signals. The application of a normal distribution to the signals probabilistically is to filter out unreliable signals and thus use reliable signals in estimating a position of a target. The primary idea of this process is similar to a recurring mathematical algorithm, particle filtering, which is related to signal processing and Bayesian statistical inference. However, the proposed algorithm is simpler in its mathematical details and is designed to facilitate real-time computational processes that are critical to the processing unit in a smart device;

examples of simplicity include no normalization of particles, no use of prior data, no measurement update, and no issues with the weight disparity, which is a common problem in particle filtering. To evaluate the effectiveness of the developed algorithm, this study compares it with two conventional positioning algorithms. The comparison is based on various simulations that emulate tracking scenarios with various levels of measurement errors, which are to reflect various degrees of signal interference. The development and assessment of PLS are sequentially illustrated in the following sub-sections.

5.4.1 Initiation of the PLS algorithm

The start of a new cycle in estimating position, except for one case of the very initial position estimation, stems from the previous position estimation. Because PLS is a probabilistic position estimation, it starts by generating random points around the previous position. To generate random points while guaranteeing that the developed tracking system will operate in real time, the algorithm needs to determine two factors: the range of random points and the number of points in the generation of random points, each of which contribute to the real-time performance of the system. The range of the random point generation takes account into the possible range of the target's speed. That is, the range is composed of the range estimated by the speed of the target and an additional buffer. The developed tracking system, which targets to track a human subject, uses a range that is equivalent to 3 meters per 0.7 seconds, which is a conservative range, compared with a fast walking speed of a human subject (Mohler et al. 2007). To determine the number of points in each interval of position estimation, extensive experimental laboratory tests are performed with multiple smart devices, such as latest smartphones and smart tablets. The PLS algorithm shows reliable real-time performance with 900 points during an update interval of 0.7 seconds. Thus, 900 points is selected as the number of random points for each time of evaluation. Figure 11 shows a detailed view of the generation of random points (left) and sequential generations of points (right) during real-time tracking.

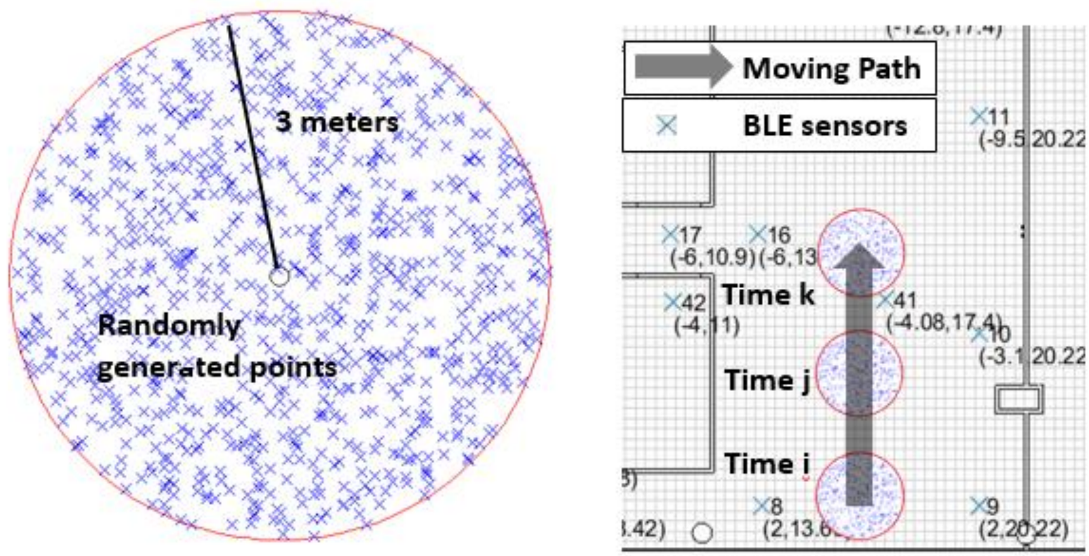


Figure 11: Generation of random points

5.4.2 Execution of PLS

PLS probabilistically evaluates multiple points that are near the previous position to find the current position estimation. Using the signal-processing method (Equation 1), signal propagation relationship (Equation 2) and the obtained probability model (Equation 3), PLS quantifies the likelihood of all signals for each of the points. For simplicity in this quantification, PLS uses RSSI values instead of the corresponding computed distance values, so Equation 7 shows the relationship between distance and RSSI, which is rearranged from Equation 2. Then, Equation 7 converts distance data between a candidate point (x, y) and the sensor of interest to the corresponding RSSI, which is considered as an expected RSSI in this context. Then, to evaluate the likelihood of a measured RSSI for the candidate point (x, y), the expected RSSI is compared with the measured RSSI by the normal probability distribution model (Equation 8). Because each position estimation involves multiple sensors and 900 random points, PLS repeats this process for all sensors detected at the same time interval and for all of the (x, y) candidate points. After evaluating all of the RSSI signals, PLS uses Equation 9 to keep track of the point, which has the highest evaluation, which eventually becomes the next position estimation.

$$\overline{RSSI_{i,j,k}} = -|RSSI_1| - \log(Dist_{i,j,k}) * 10n \tag{7}$$

i: sensor index
j: position index j for $(X, Y)_j$

k: time index
$\overline{RSSI_{i,j,k}}$: expected RSSI for sensor i at position j at time k
$Dist_{i,j,k}$: actual distance between sensor i and point j at time k

$$P_{i,j,k} = normpdf(x, \mu, \sigma) = normpdf(\overline{RSSI_{i,j,k}}, RSSI_{i,j,k}, \sigma_{i,j,k}) \tag{8}$$

$$(x, y)_k = \underset{all\ (x,y)_j}{\operatorname{argmax}} \left(\sum_{all\ i} P_{i,j,k} \right) \tag{9}$$

To illustrate the process of PLS and, Figure 12 (left) provides an example that describes a simple two-dimensional evaluation with three sample beacons, each of which are marked by x and have distance measurements, each of which are indicated by a circle. Each circle on the curve in Figure 12 (right) indicates the evaluation of a point among many. Among many evaluated points, Equation 9 searches for the maximum value for selection of the position, which is (5.01, 4.41) in this case.

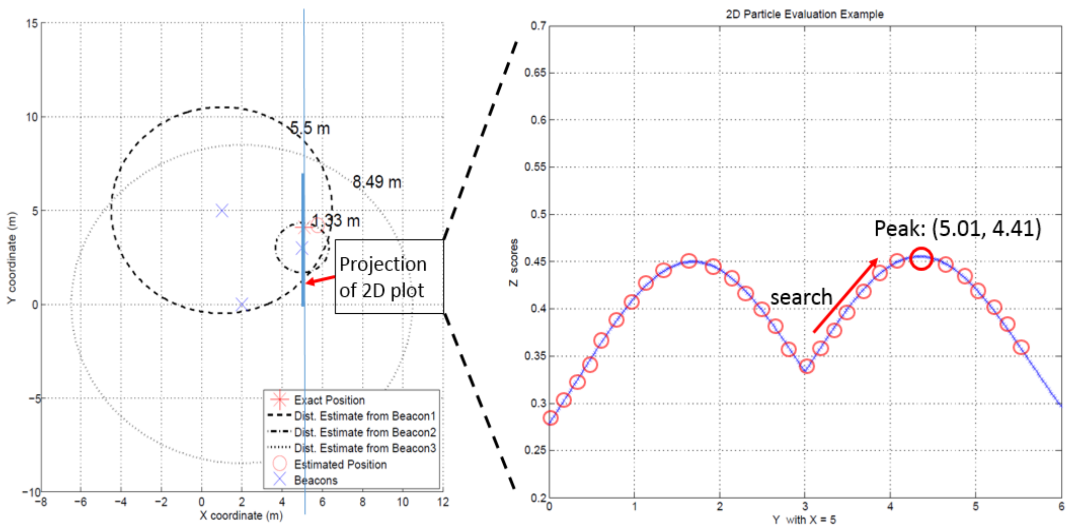


Figure 12: PLS evaluation in a 2D view

A position (at time k) of a subject is dependent on the previous positions (at times k-1, k-2, …, 1) of the subjects as shown in Equation 10. However, to simplify this relationship, PLS assumes a specific relationship between the previous position (time k-1) and the next position (time k) estimations that the subject can move within a movable boundary; this movable boundary has been discussed previously with the range of random points. This assumption simplifies their relationships and is expressed by a Markov Chain model as shown in Equation 11. Using this relation and Equations 1, 2, 7, 8, and 9, the position of the subject is updated in real time.

$$P(XY_{k+1} = xy_{k+1} | XY_k = xy_k \cap \ldots \cap XY_1 = xy_1) \tag{10}$$

$$P(XY_{k+1} = xy_{k+1} | XY_k = xy_k) \tag{11}$$

5.5 Experiments and Results

To demonstrate the performance of PLS, an experimental methodology is established. Figure 13 shows this methodological procedure that presents the overall process of this experiment. The validation of the developed algorithm is performed through 1) on-site data collection, 2) computational simualtion, 3) execution of algorithms, and 4) error analysis. The same construction site (shown in Figure 6) is used to collect two sets of data samples that form the basis of the following computational simulation. The two scenarios are designed to create different levels of proximity between the receiver and the transmitters, which intends to assess, with the computational simulation, the reliability and robustness of the developed algorithm. The computational simulation for each of the scenarios generates signals with a wide range of signal errors, which are variations of the sample data sets collected onsite. Testing of various levels of error is particularly important because it offers the ability to assess the developed algorithm in various situations; every construction site is unique and has various levels of signal interference. Because of time and physical limitations for conducting multiple field tests at construction sites, this study adopts a method of computer simulation with on-site data collection from a simple path

(Figure 14) at a construction site. The complexity of the path is not critical in the assessment of the algorithm because of the additional computer simulation; complex paths tend to yield unreliable signals resulting from multi-path and signal degradation, which are incorporated by the computer simulation.

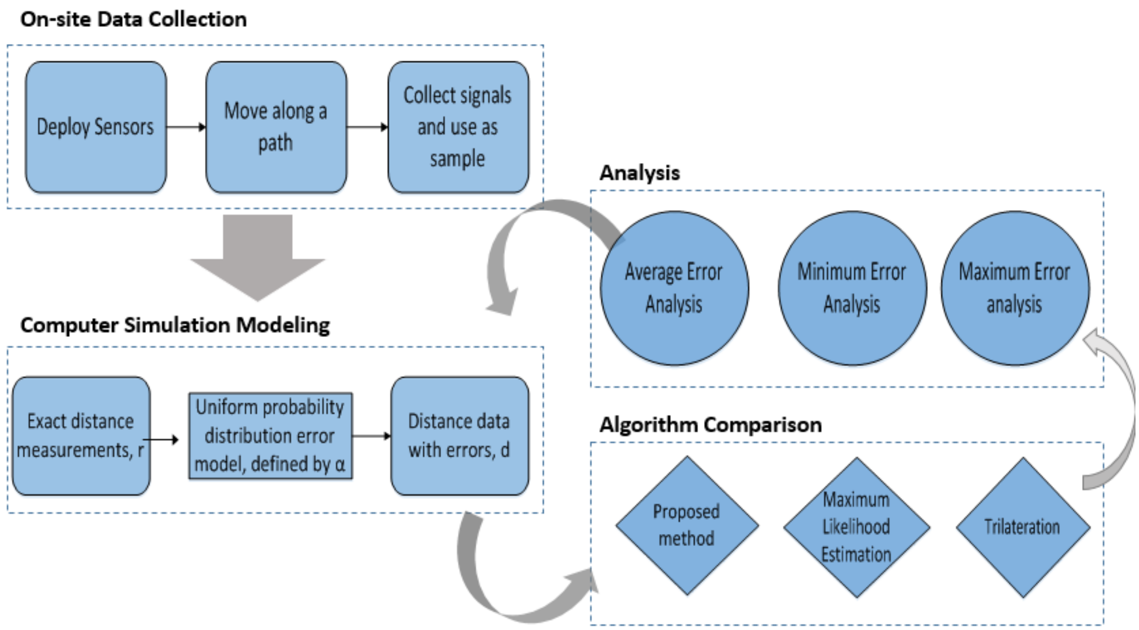


Figure 13: Experimental methodology

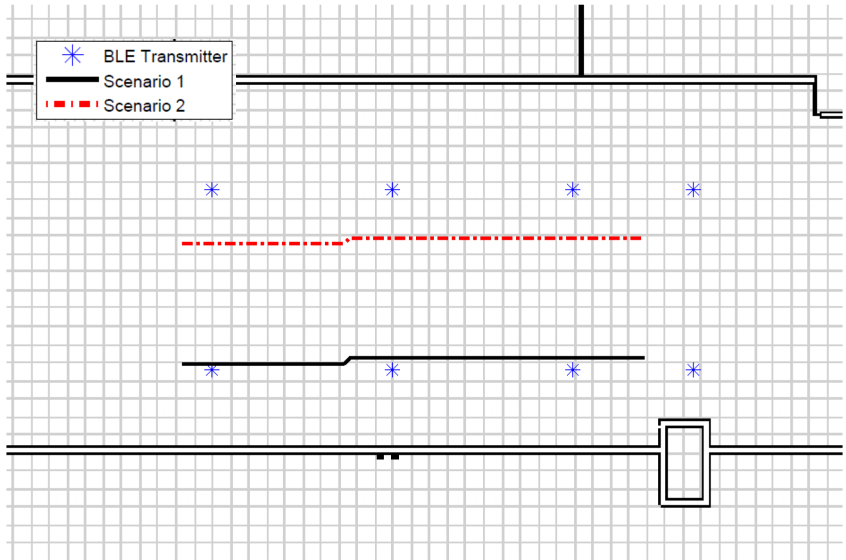


Figure 14: Simple path test scenarios

For each of the two scenarios, the computer simulation generates 16 variations of signal error, which is the error in distance normalized by the actual distance, ranging from 0.01 to 1.5. For example, the case of 1.5 implies that the average errors in distance is 1.5 times as larger than the actual distance. For each of these test cases, 76 points are statistically evaluated. In addition to assessing the PLS algorithm, the analysis assesses two common distance-based positioning algorithms (i.e., trilateration and MLE) subjected to the same test cases to serve as a benchmark for comparison. Figure 15 shows the estimated trajectories based on the computed 76 points for one case.

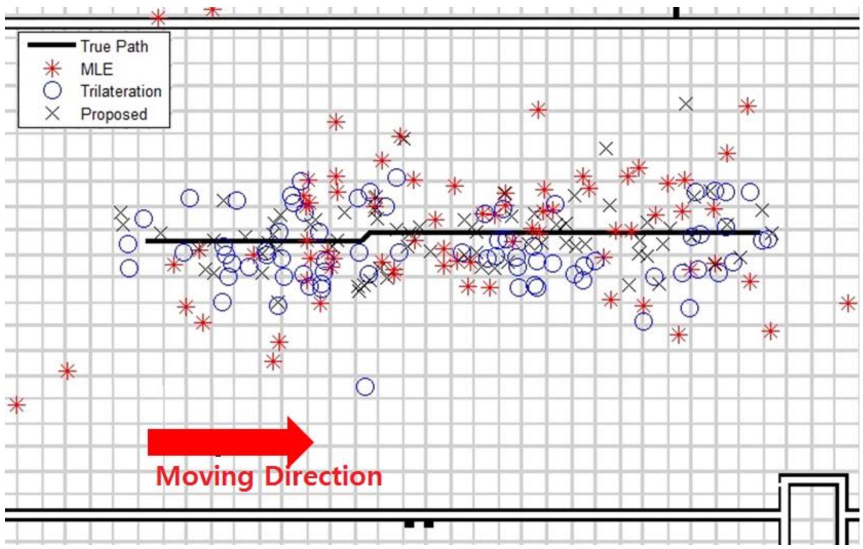


Figure 15: A result plot for one of the computer simulations

Such results presented in Figure 15 are further examined with respect to the minimum, average, and maximum errors of each of the algorithms. Figure 16 shows the results of this examination. The x-axis in each of the six plots in Figure 16 is the rate of distance error normalized by the exact distance. The left three plots represent the average, maximum, and minimum errors for scenario 1, and the right three plots represent those errors for scenario 2. The results reveals strong evidence that the error in position increases with an increase in error rate for all of the distance-based positioning methods. While this is true for all of the methods, the results of the proposed algorithm present a significant advantage: increased error in distance considerably degrades the position estimation of the other two methods while they only minimally affect the result of the proposed algorithm. This benefit of the proposed algorithm is rooted in the probabilsitic signal filtering process. Unlike the other distance-based algorithms, which rely on measured distance data to estimate position in their own criteria that minimize errors, the proposed algorithm probabilistically evaluates distance measurements prior to estimating position of the target. This probabilistical evaluation of received signals can significantly reduce the error in position estimation, especially when the received signals contain significant noise resulting from the signal interferences such as degradation, multi-path effect, and line-of-sight problems.

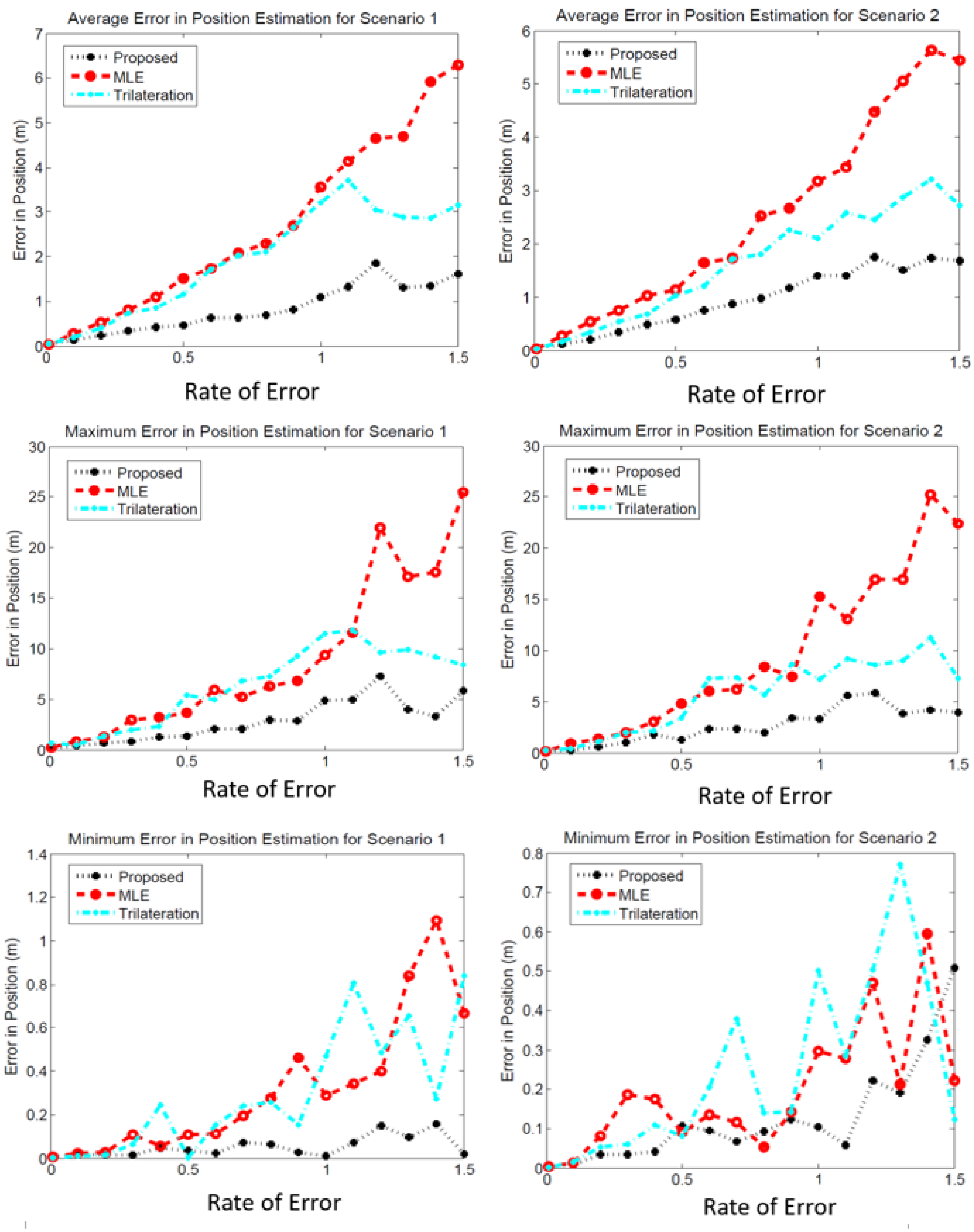


Figure 16: Error analysis, compared with two conventional methods

5.6 Chapter Summary

The existence of a multitude of interactions among workers, equipment, and materials at a construction site results in signal interference that appears in various forms, such as signal degradation, occlusions, obstructions, and multi-path effects. Such signal interference adversely affect the propagated signals of radio signal-based sensing technology, resulting in difficulty in tracking a target. To address this issue, this study conducted a fundamental study with RSSI behavior analysis, and developed the PLS algorithm using the result of the fundamental RSSI study. The developed PLS algorithm was assessed with respect to accuracy, reliability, and robustness through on-site data collection and computer simulations. The results of the test suggested that the PLS algorithm outperformed the two conventional positioning algorithms. Improved performance of PLS became more significant when the received signals experienced higher levels of noise resulting from the signal interferences in a testing environment. The observed advantage of PLS is found because of its ability to probabilistically filter out unreliable signals and use relatively reliable signals in the process of position estimation. In sum, the contribution of this new algorithm development to the body of knowledge is as follows: 1) reducing the gap in knowledge of the behavior of RSSI when a RSSI-based system is used in a noisy environment like an indoor construction site and 2) creating a new probability-based algorithm that accounts for signal interference issues that are frequently observed.

CHAPTER 6. AN INTEGRATED TRACKING APPROACH

6.1 System Components

To develop a system that minimizes the errors of various sensor components, this research adopts an integrated approach in the development of the tracking system. This system uses three major components, each of which collect/use unique information/data; the three components are 1) a BLE-based technology that provides absolute positioning data, 2) motion sensors that provide relative positioning data, and 3) BIM that provide semantic geometric data. Figure 17 shows the system architecture, which describes the individual components and their integration into a single software platform. The integration part is responsible for combining and processing the collected data/information in real time through developed integration modules that are discussed in the following sub-sections.

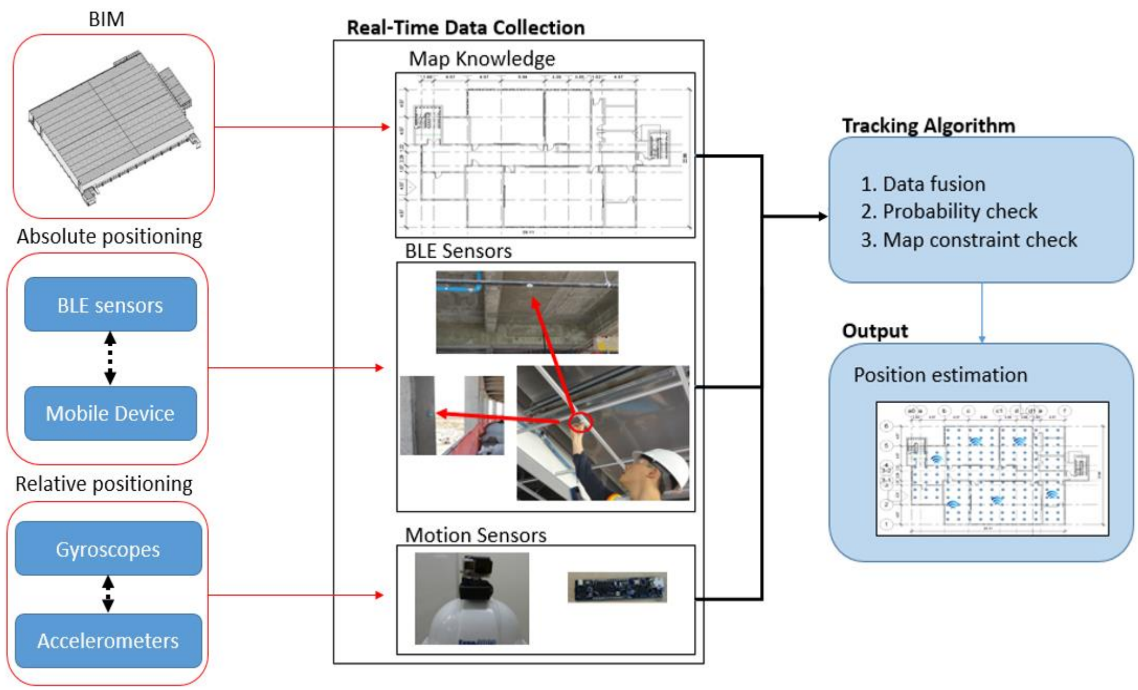


Figure 17: System architecture of the integrated tracking system

6.1.1 Absolute Positioning Data

This sub-section pertains to the establishment of the basis tracking module through the absolute positioning system, BLE. The BLE tracking component used in this integrated system is identical to the BLE tracking system discussed in CHAPTER 5. For this reason, this sub-section briefly summarizes the major equations of the BLE tracking system on which the other components are added for improved accuracy.

As soon as the BLE receiver receives RSSI from detected BLE transmitters, it processes the signals based on Equation 1, which generates processed RSSI values. In the meantime, Equation 7 computes the expected RSSI values for the position of a candidate point and the locations of the detected BLE transmitters. Following this, Equations 8 and

9 assess the likelihood of all of the candidate points for being the next position estimate by comparing the processed RSSI values with the expected RSSI values. This process probabilistically evaluates all of the received signals by keeping tracking of the most likely point and generates an estimate of position. Equation 12 summarizes these processes and denotes its result as $(x, y)_{BLE}$.

$$(x, y)_{i_{BLE}} = \underset{(x,y) \in XY}{\operatorname{argmax}} \left(\sum_{all\ signals} P(RSSI_e, RSSI_r) \right)_i \tag{12}$$

P(x,y): probability model given x and y
$RSSI_e$: expected RSSI
$RSSI_r$: received RSSI
i: time step i

6.1.2 Relative Positioning Data

To provide relative positioning data, this research uses motion sensors as the second component of the hybrid-tracking system. Motion sensors are usually composed of three types of sensors (i.e., accelerometers, gyroscopes, and magnetometers). Although motion sensors collect accurate data when these three sensors operate together through state-of-the-art algorithms, they suffer from distortion in data when the magnetometers are subjected to external magnetic influences. Construction sites typically contain materials that cause such magnetic influences, so it is critical that researchers remove this adverse effect from magnetic distortion. For this reason, the developed system uses only gyroscopes and accelerometers in its development of relative positioning.

To obtain relative movement data from a reference point, the second component obtains the heading direction and the number of steps. Figure 18 shows a schematic perspective of the used methodology to find the accumulated number of steps from the motion sensors. When the motion sensors operate to compute the accumulated number of steps, it may mistakenly add extra steps upon desired shaking of the sensors. To eliminate such mistakenly computed steps, the algorithm uses the step and time thresholds for filtering out minor shaking that could have been identified as a step otherwise. The data in Figure 18 show the results of a walking test where a test subject walks 30 steps and collects the acceleration data. The circle and cross marks at peaks and valleys of the plot indicate detected steps. Equations 13 and 14 show the process of computing the relative movement given the number of step and the heading direction and the position estimation by the motion sensor component.

$$(\Delta x, \Delta y)_{motion} = (N \times \cos(\theta), N \times \sin(\theta)) \tag{13}$$

θ: heading direction
N: number of step

$$(x, y)_{i_{motion}} = (x, y)_{i-1} + (\Delta x, \Delta y)_{motion} \tag{14}$$

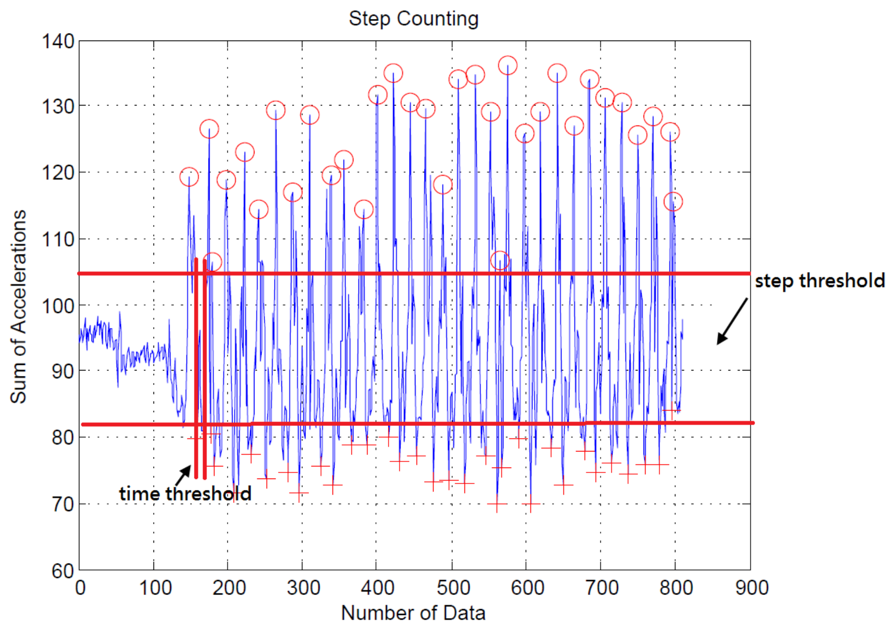
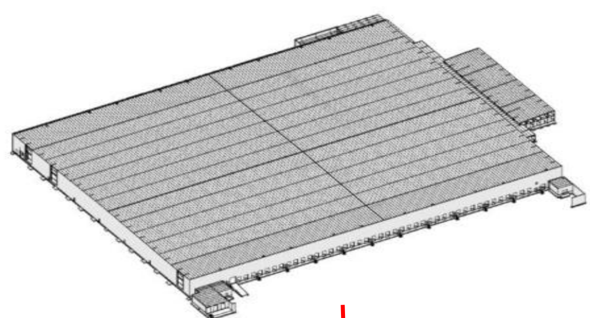


Figure 18: Step counting profiling and implementation

6.1.3 Geometric Semantic Data

For the third component of the proposed hybrid-tracking system, this research uses geometric data from a BIM model. To generate geometric constraint data, BIM geometric and object information are extracted from a BIM model and imported into the tracking system. Figure 19 shows an output of extracted BIM data that is integrated into the tracking module of the system. These data provide the tracking module with semantic map knowledge that improves the tracking accuracy of both the absolute and relative positioning data. It becomes useful in two cases. First, the fluctuation of RSSI signals may cause the absolute position estimation to move across two different spaces by passing through a geometric constraint, such as a wall. Second, one of the well-known problems of IMU sensors, drift, may occur and generate the relative position estimation to continuously move towards a geometric constraint and eventually pass through it. These are unlikely movements that occur because of the measurement error of the sensing components. By imposing such geometric constraints, the system can detect false movements and mitigate the negative impacts from these movements. However, improperly used geometric constraints can lead to a problem of being trapped in a confined space. This problem can be resolved by relaxing the near-by constraints to allow for movement from a space to another space through a door and an object with an opening. To relax the geometric constraints, this study uses an extra buffer on either sides of doors to allow an extra space to account for the uncertainty in position estimation.



Building Geometry Data


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Figure 19: BIM data extraction for integration

6.2 Knowledge-based Integration for Error Correction

Following the developments of the individual system components, the research develops a framework that combines the components in a knowledge-based error correction module. Figure 20 presents the framework for this module that combines the three system components interactively in its efforts to correct errors. The interaction is based on prior knowledge of the components as follows: 1) The BLE-based tracking component provides absolute position information, but this information suffers from significant fluctuation due to noisy data, 2) the motion sensor component provides relative position information, but this information suffers from a drifting problem caused by accumulation of errors in motion data, and 3) the BIM geometric semantic data provides map knowledge that can be used to improve the accuracy of the tracking components.

The challenges for the BLE-based and motion-based tracking components can be heuristically addressed through the developed error correction module. Data collected from motion sensors, which provide directional information, can assist to correct the fluctuation in the absolute positioning system. In addition, the drift problem in the motion sensors can be corrected by extracting the moving trends of a target from the BLE-based tracking component. Such cases are modularized by certain rules that quantitatively describe the challenges as shown in the rule module in Figure 20. After checking the rules, the hybrid-tracking system fuses the estimations from the two tracking components by a low-pass filter as shown in Equation 15. At the initiation of the application, the weight in Equation 15 is set to a certain value from 0 to 1. As the system makes decisions through the error correction module, it modifies the weight (α) by increasing or decreasing depending on the error correction criteria.

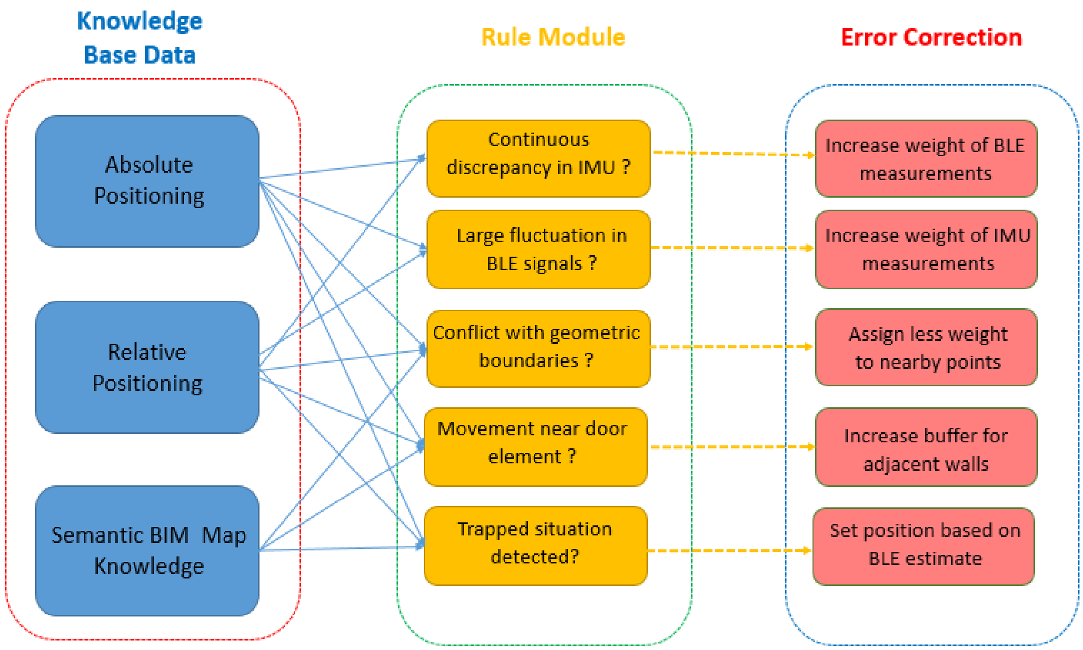


Figure 20: Framework for a knowledge-based error correction module

$$(x, y)_i = (1 - \alpha)(x, y)_{i_{BLE}} + \alpha(x, y)_{i_{motion}} \tag{15}$$

Figure 21 depicts the details of the system interaction from data acquisition to action. After the data acquisition step, the system interaction step takes place to find exceptional cases that need additional handling processes. One example is the case of trapping. Near the transition between spaces, the position can erroneously be estimated. If this proceeds continuously, the system will receive a strong indication that the subject is in fact in a different space. Then, the action step corrects the position by updating it with the latest estimate by the BLE component instead of using the previous trapped position. In addition to the problem of trapping, accumulation of drift in the motion sensor can also result in a discrepancy. Up to the detection of this event, the system continuously examines whether the event persists. If the estimates by the IMU sensor are continuously detected to be biased compared with those by the BLE sensors, the system applies heuristic error correction mechanisms by adjusting the heading direction to correct the drift. When adjusting the heading direction, only a small fraction of the discrepancy is corrected at each time interval until the discrepancy is no longer detected.

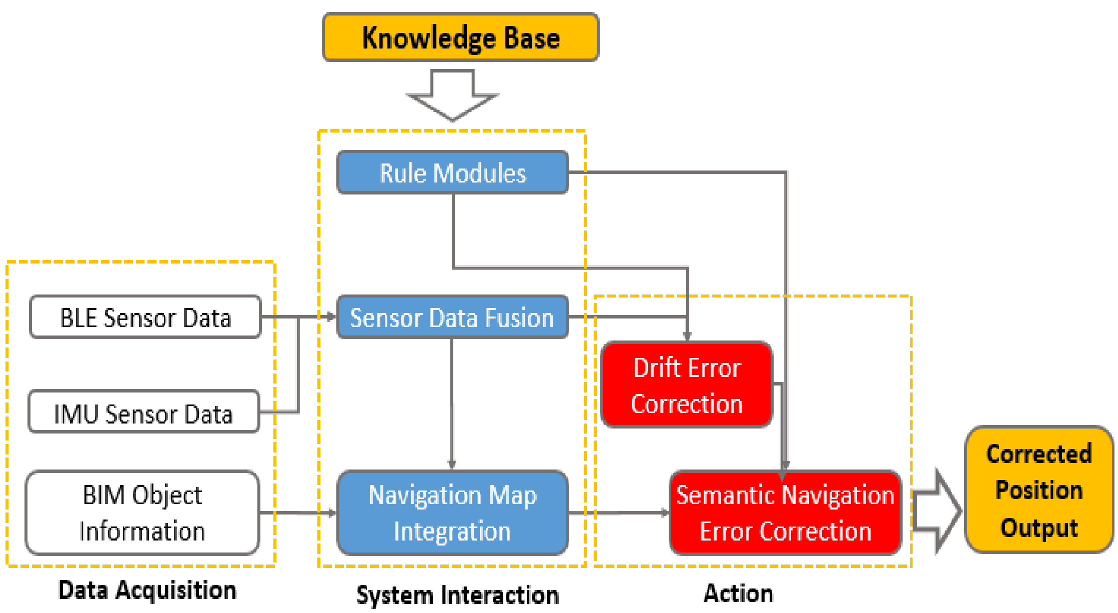


Figure 21: Interaction of the system components

6.3 Experiments and Results

This section presents two sets of field experimentations. They have been carried out in different times at different locations with different system settings. The major differences in the two experimentations are the system deployment plan; the first test deploys BLE sensors at a density of approximately 57 m^2 per sensor while the second test deploys BLE sensors at a density of approximately 23 m^2 per sensor.

6.3.1 Experimental Test 1

To evaluate the developed hybrid-tracking system, this study selects an indoor construction site and conducts tests in various conditions to observe the performance of the system. Figure 22 shows the selected construction site, which is a building construction site located in Atlanta, Georgia. The site is selected such that the test is performed in a normal working condition of a construction site. Testing of a tracking system in such an environment is crucial for validation of a tracking system because the environment presents challenges caused by line-of-sight issues, occlusion and other signal interference from dynamic interactions of construction assets (e.g., material, workers, and change of layout). In addition, the test is carried out during the hours of construction operation to emulate a more realistic situation. Figure 22 shows the actual construction site and a 2D top-down view that displays the installation locations of the BLE sensors. Twenty BLE transmitters are deployed over the site, and they are indicated by an X mark on the 2D top-down view. Note that the nature of the construction site may not allow the system deployment to be made as desired (e.g., symmetric deployment of sensors). This requires the ability of a tracking system to be flexible and adjustable in its deployment layout for a full-scale construction site implementation. Consequently, this study changes the deployment plan from a density of 25 m^2 per sensor, which is the original plan, to 57 m^2 per sensor, which is the changed plan, to meet the site requirement.

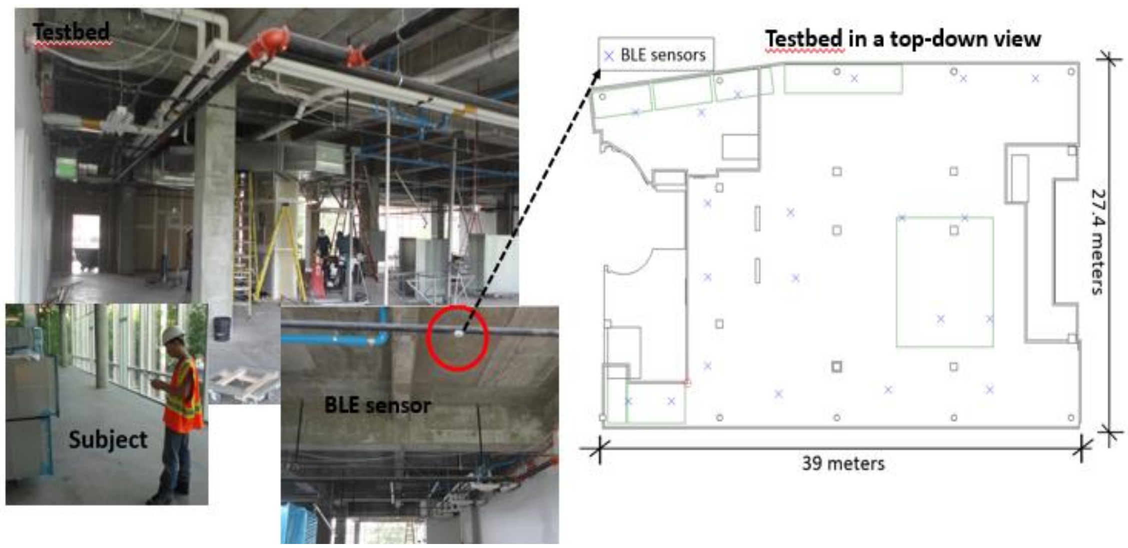


Figure 22: Construction site testbed and its 2D view for experiment 1

This research conducts field experimentations with two scenarios, each of which are approximately 100 meters long with many numbers of turns at various angles. The intention of the designed scenarios is to introduce complexity to sensory data of the motion and BLE sensors. Inclusion of complex movements, which exacerbate drift in the motion sensors and signal interference/degradation of BLE signals, is to emulate a more realistic situation, compared with simple movements. Furthermore, to test the reliability of the tracking system for movements in between spaces, one of the scenarios includes movements in and out of rooms to create conditions that are more challenging. Figure 23 exhibits the ground truth of the two scenarios indicated by black straight lines and the moving direction by red arrows.

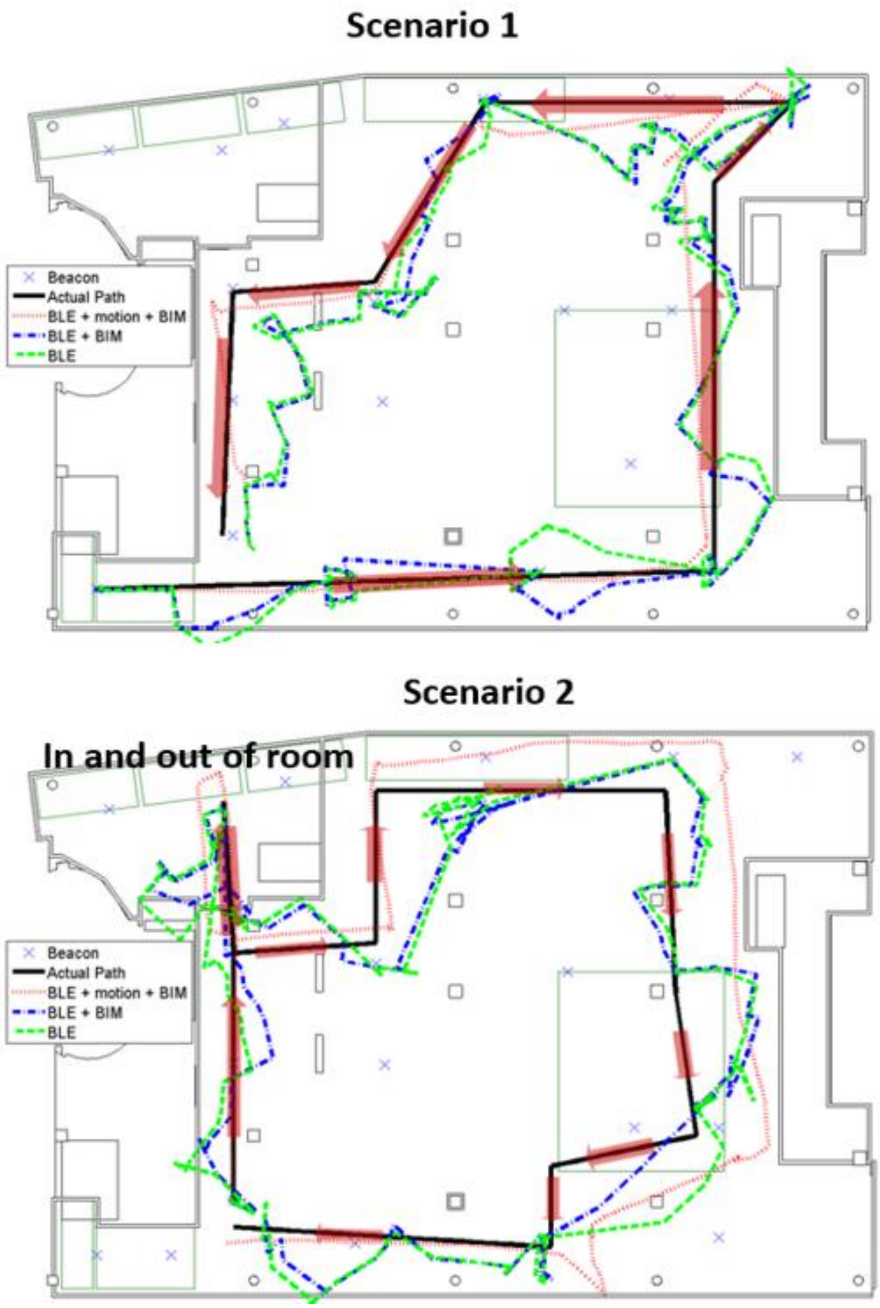


Figure 23: Tracking tests and results for experiment 1

To investigate the effect of each of the tracking components on the overall tracking accuracy, approximately 8,000 data points are collected and approximately 200 position estimates are statistically analyzed for each scenario. The analysis mainly examines the accuracy of the tracking system by comparing the results with the ground truth. In measuring the ground truth, time is logged at every critical point (i.e., every turning point) as a subject walks along the designed paths. Intermediate points between critical points are linearly interpolated as the subject walks at a constant speed. Results that are compared with the ground truth are classified into three categories—they are BLE, BLE + BIM, and BLE + BIM + motion sensor—to quantify and examine the effect of each component in the accuracy of the hybrid-tracking system.

Table 4 summarizes the results of the statistical analysis for scenarios 1 and 2 with respect to maximum, minimum, and average errors, and standard deviation. For most cases, it is observed that the additions of components result in improvement in accuracy and precision of the tracking results. The effect of the BIM knowledge decreases the average position error from 2.31 meters to 2.26 meters while the effect of the motion sensor decreases the error to 1.15 meters. Similarly, the effect of the BIM knowledge in Scenario 2 decreases the average position error from 3.21 to 3.07 meters while the effect of the motion sensor decreases the error further to 2.03 meters.

Table 4. Statistical analysis for Scenarios 1 and 2 for experiment 1

Scenario	Error Type	Error (m)		
		BLE	BLE + BIM	BLE + motion + BIM
1	Maximum	6.94	7.50	3.23
	Minimum	0.02	0.06	0.01
	Average	2.31	2.26	1.15
	Standard Deviation	1.61	1.62	0.72
2	Maximum	8.36	8.85	4.51
	Minimum	0.09	0.01	0.01
	Average	3.21	3.07	2.03
	Standard Deviation	1.97	1.88	1.22

Table 5 lists the percentage improvement of accuracy with respect to the average and standard deviation of the position errors. It shows clear evidence of improvement in all cases although the effect of the BIM knowledge is minimal in the test cases. On average, the average position error and the standard deviation of the position error are improved by 42% and 45%, respectively. Figure 24 depicts two exemplary situations that the BIM geometric semantic knowledge positively influences the position estimation by detecting and correcting a false movement. The test cases minimally encounter such situations, so the improvement by BIM is shown relatively small in our test cases; however, if tests are conducted such that these types of cases are found often, then it would considerably enhance the accuracy of tracking.

Table 5. Percentage improvement of accuracy for experiment 1

Scenario	Improvement by BIM		Improvement by BIM + motion	
	Average Position Error	Standard Deviation of Position Error	Average Position Error	Standard Deviation of Position Error
1	2%	0%	49%	55%
2	4%	5%	34%	35%
Overall	3%	2%	42%	45%

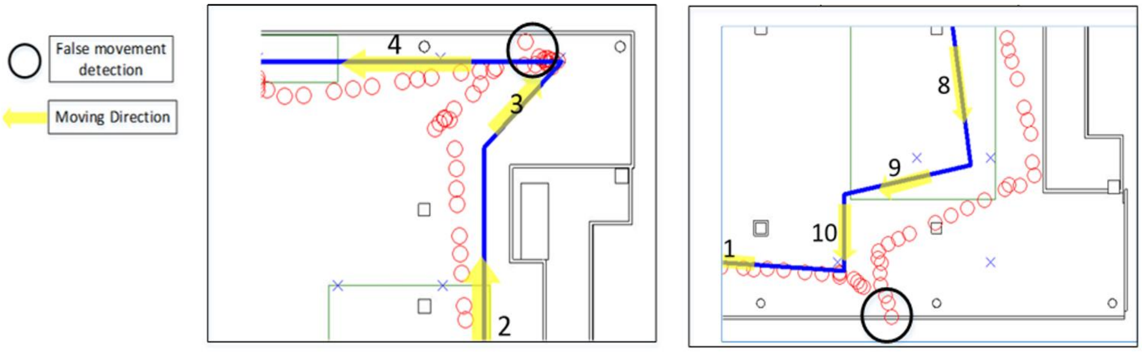


Figure 24: Position error correction by map knowledge

6.3.2 Experimental Test 2

As an additional test for evaluating the developed hybrid-tracking system, this study conducts tests in a similar indoor site but with different system deployment plans. Figure 25 (left) depicts the selected construction site, which is a building construction site located in Lincoln, Nebraska. Figure 25 (right) also shows a 2D top-down view of the site. The size of this site, compared with that of the site from experiment 1, is slightly larger. To introduce variations to the system settings, significantly more numbers of BLE transmitters, which is 47, are deployed over the site. This deployment plan results in a density of approximately 23 m^2 per sensor.

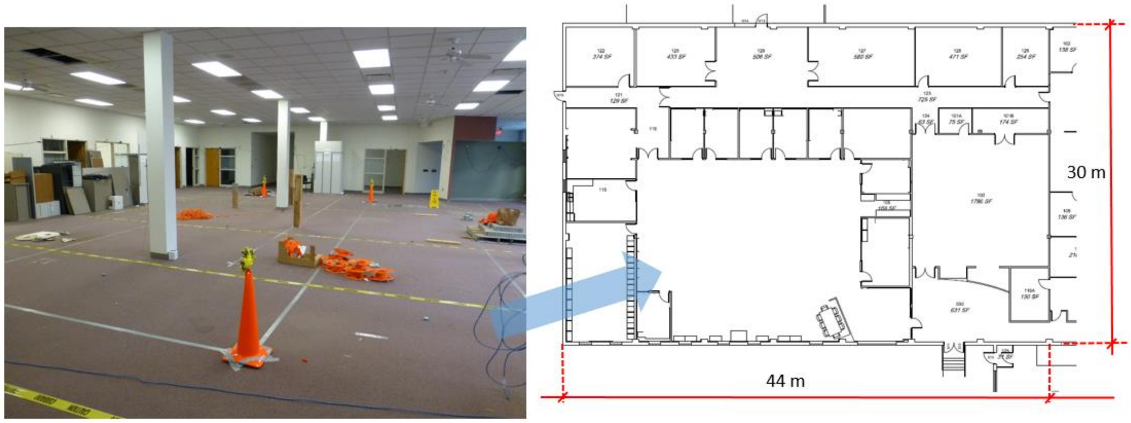


Figure 25: Construction site testbed and its 2D view for experiment 2

Similarly to experiment 1, experiment 2 involves five scenarios, each of which present different levels of sources of signal interference caused by line-of-sight issues, occlusion and other signal degradation. A UWB tracking system is also subjected to the same experimental trials to serve as a benchmark for comparison. Inclusion of changes in spaces and relatively complex areas in the tested paths is to assess an important parameter that a tracking system should perform satisfactorily with; as discussed in the literature review, many systems do not perform adequately in complex environments where line of sights is interfered. Figure 26 exhibits the ground truth of the five scenarios indicated by blue lines.

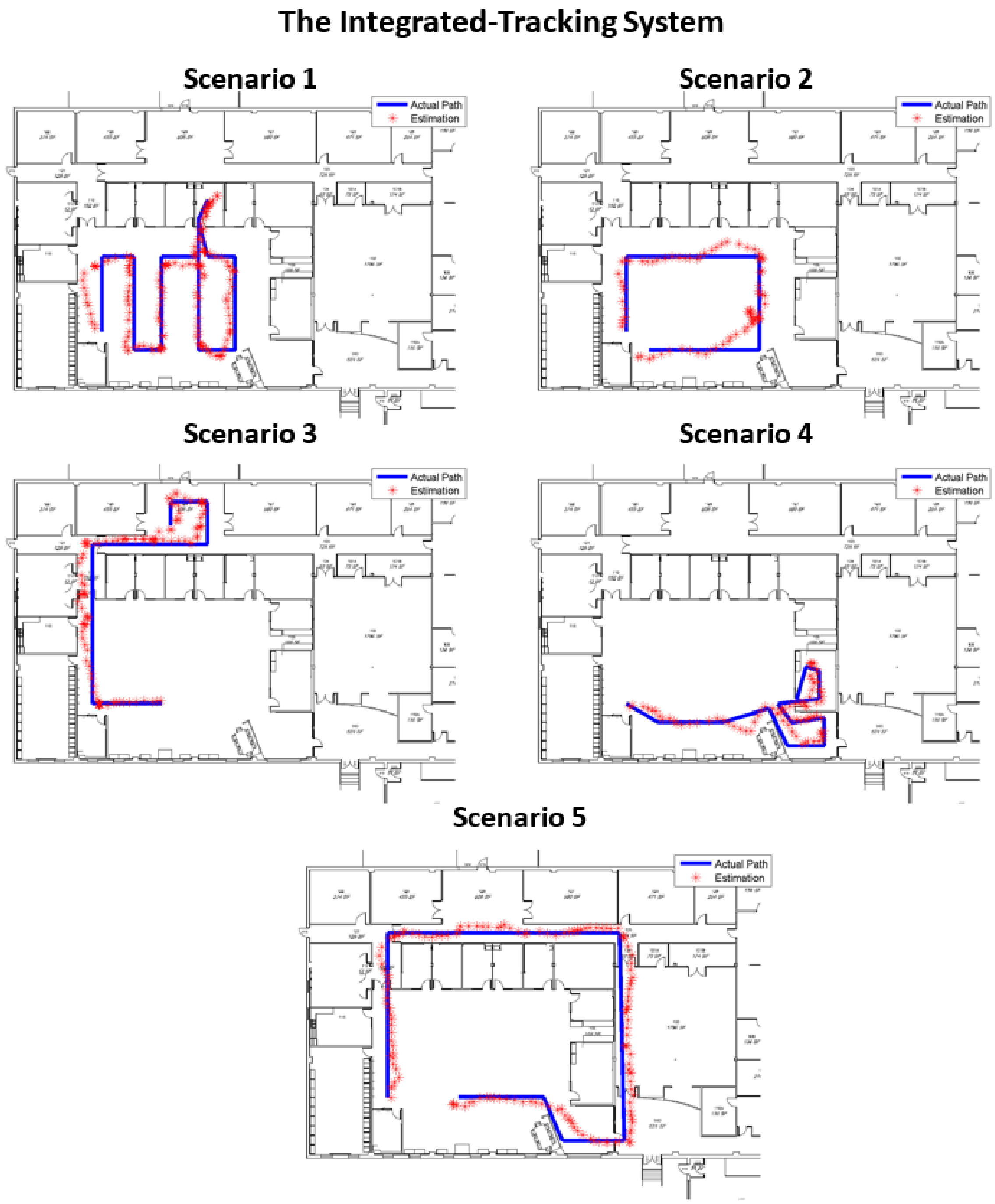


Figure 26: Tracking tests and results for experiment 2 using the integrated approach

Figure 26 shows the estimated positions by the integrated-tracking system on the 2D view of the site map. For quantitative evaluation, the same method of analysis, which is used for experiment 1, is used to examine the collected results of estimation for experiment 2. The analysis mainly investigates the accuracy of the integrated-tracking system by comparing the results with the ground truth. In measuring the ground truth, time is logged at every critical point (i.e., every turning point) as a subject walks along the designed paths. Intermediate points between critical points are linearly interpolated as the subject walks at a constant speed. Similarly, Figure 27 shows the results of the UWB tracking system for the first four scenarios; the UWB system fails to track a subject in scenario 5 because of the range limit. The UWB system performs accurately in an open space as is seen in scenarios 1 and 2; although it fails to track the subject when the subject enters the room in scenario 1, the performance is reliable elsewhere. However, the observation of the results in scenarios 3 and 4 reveals that the performance of the system is highly unreliable in relatively close spaces that present line-of-sight issues; the system fails to track the subject at many locations. Because of lack of data for the UWB system in many cases, the following analysis excludes detailed discussion on UWB and a direct comparison of the performance of UWB and that of the integrated system. Note that the following discussion focuses only on the integrated approach.

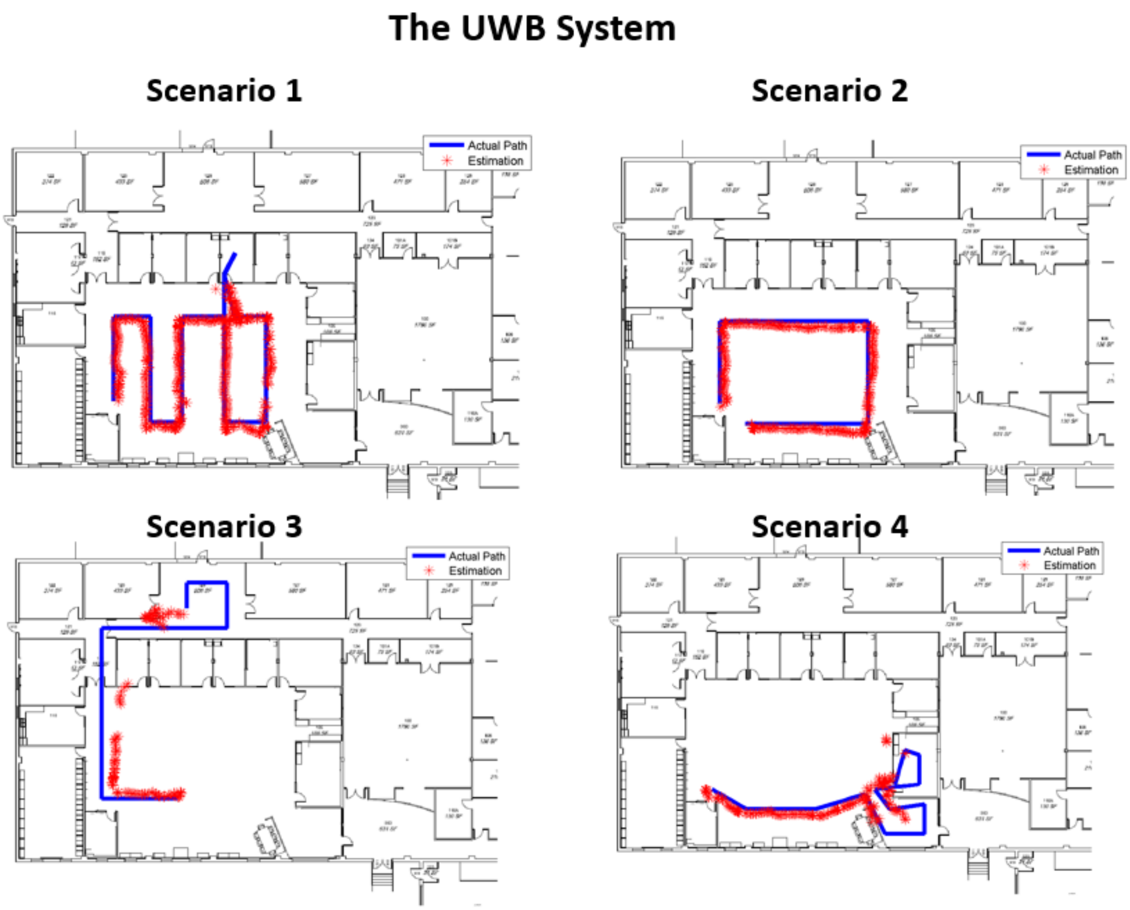


Figure 27: Tracking tests and results for experiment 2 using UWB

Table 6 summarizes the results of the statistical analysis for the five scenarios with respect to maximum, minimum, and average errors, and standard deviation. For most cases, the results present clear evidence of the system interaction in effort of correcting errors in each of the components. Although the result of scenario 3 is slightly better than those of the other scenarios, all of them are relatively comparable in all of the compared metrics. The constant performance of the hybrid tracking system reveals an important finding that the system is not significantly affected by the complex geometry of the site layout and the corresponding signal interference.

Table 7 compares the results of experiment 1 and those of experiment 2 in regards to percentage improvement. The results indicate clear evidence of improvement resulting from denser sensor deployment. On average, the average error and standard deviation are improved by 26.4 % and 29.9 %.

Table 6. Statistical analysis for the five scenarios for experiment2

Scenario	Error (m)			
	Average	Standard deviation	Maximum	Minimum
1	1.21	0.73	4.20	0.03
2	1.33	0.81	4.44	0.01
3	0.90	0.51	2.81	0.05
4	1.17	0.67	3.79	0.01
5	1.24	0.65	4.88	0.12

Table 7. Comparison of the two experiments

Error	Experiment 1	Experiment 2	Improvement
Average	1.59 m	1.17 m	26.4 %
Standard Deviation	0.97 m	0.68 m	29.9 %

6.4 Chapter Summary

Sensing and tracking have been important research topics over the last decade because of their potential benefits. By acquiring reliable sensing and tracking systems, various construction applications using such systems can be developed to benefit the construction industry. However, limited research efforts were found in integrating multiple sources—that can be used for tracking—and in analyzing their effectiveness in acquiring accurate location awareness especially when applied in a dynamic, complex indoor construction site. This study presented the development of a hybrid-tracking system by integrating BLE, IMU, and BIM and examined their effects on improving the accuracy and reliability of the system. To demonstrate the performance of the developed tracking system, two sets of field experimental trials were performed at a full-scale indoor construction site. With the used system settings, the system showed an average accuracy of 1.59 and 1.17 meters for the sets of experimental studies**.** The analysis of experiment 1 indicated that the developed approach in the hybrid-tracking system reduced the average positioning error by 43% and the standard deviation of the positioning error by 45%. Furthermore, the analysis of experiments 1 and 2 presented another finding that a denser sensor deployment plan improved overall accuracy and reduced variation by approximately 28%; in general, this holds true because a deployment plan with denser sensor layout provides more reliable BLE signals. In sum, the development tracking approach demonstrated clear improvements of the tracking performance in accuracy and reliability.

CHAPTER 7. A ZONE-BASED SAFETY RISK ANALYSIS MODEL

ZBSR of individual workers is developed by 1) establishing hazard models, 2) identifying the exposure relationship between workers and associated hazards, 3) formulating a quantitative relationship between the associated hazards and modeling parameters, and 4) incorporating all of the parameters to compute an index that represents the safety performance of the worker. In the demonstration of the ZBSR model, this study discusses field experiments of the automated safety performance evaluation system, which integrate the tracking and the safety analysis components. This integration fulfils the last step of evaluating the safety performance of individual workers based on their location data collected by the tracking system. The following sub-sections introduce sequential discussions of these processes.

7.1 Hazard Model and Registration

The safety performance of workers is assessed with respect to previously identified hazards. Such identifications of hazards are carried out in two ways. By scrutinizing project information together with BIM and work schedules under hazard detection rules, certain hazards can automatically be identified (Kim and Cho 2015; Zhang et al. 2013). These types of hazards are often pre-identified hazards due to its nature of being automatically identified by analyzing associate project information. Unlike such hazards, there also exist hazards that cannot be automatically identified. These second types of hazards usually reflect specific project/site information that can change over time with the progress of work. Examples of these hazards include poorly maintained areas, such as poor housekeeping areas, inappropriately piled stock areas, broken barricades, and scaffolds that violate safety rules.

Upon the identification of hazards, they need to be modeled with certain parameters for quantitatively defining the hazards. Such parameterized hazard models allow evaluation of the safety condition of workers with respect to the hazards. Each hazard is different in type, size, and potential consequence, so the modeling of hazards needs to account for these factors. To uniquely describe hazards, the ZBRS model uses an safety envelope approach that has been used by previous research studies (Park et al. 2015; Shen et al. 2016; Wang and Razavi 2016). Defined hazards through this approach provide information of the core hazard and hazard envelope with respect to certain geometric information, such as radius, width and length; the core hazard is represented by a zone that must not be breached and the hazard envelope is represented by a zone that should be protected. The ZBRS model considers any breach into the core hazard as an accident and any breach into the hazard envelope as a near-miss event.

One of the leading causes of occupational injuries and fatalities is a fall from portable ladders. An a means of protection, OSHA suggest erecting a barricade around the ladder work to keep traffic away from the ladder (Occupational Safety and Health Administration 2017). Such a hazard is modeled by certain geometric shapes such as a circle and an ellipse. Other types of hazards that are modeled by a rectangular shape are large penetrations (large holes), hazardous material storage areas, restricted areas, and unsafe work zones. Figure 28 shows examples of hazards; the scaffolding hazard is a type of hazard that is identified through onsite inspection and the ladder hazard is a type of hazard that is identified through project information analysis. The modeling of the hazard to define the geometric information will be up to user discretion (e.g., safety manager, engineer). Depending on the need/desire of the envelope zone, the user can set the geometric parameters of the envelope zone from 0 to a specific range; the case of 0 is the case of a hazard that is detected by on-and-off violations. Figure 29 shows the parametric modeling of these hazards that are eventually fed into the ZBSR analysis model for safety performance assessment.

Figure 28: Hazards identified on a specific day

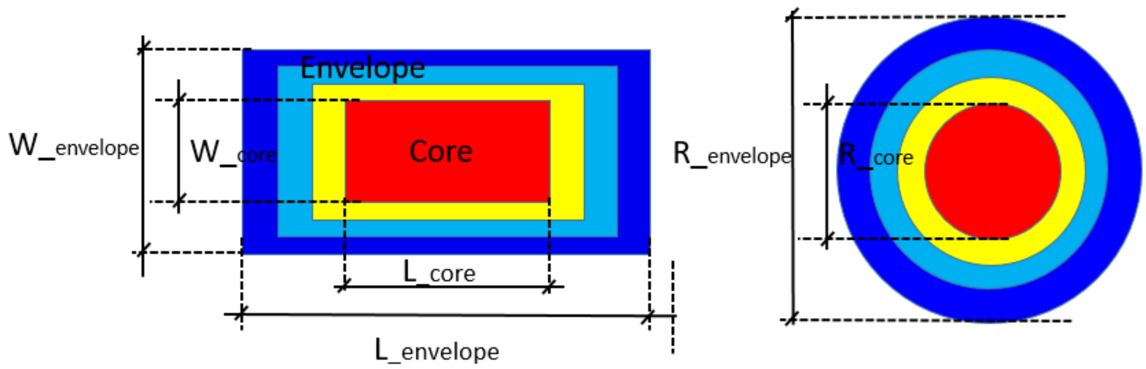


Figure 29: Parametric modeling of hazards

7.2 Evaluation Metrics

The previous sub-section has introduced the parameters, which model existing hazards with respect to specific aspects. However, to assess the safety performance of individual workers based on their location data with hazard models, the assessment system should account for dynamic location data in concrete relationship with the hazards. For example, when a worker is near a hazard, the safety condition of the worker is associated with parameters such as exposure level, exposure frequency, and degree of potential damage or injury upon the occurrence of an accident. The quantification of such parameters enables objective assessment of the safety performance of workers in a systematic way.

The quantification of safety performance requires concrete criteria/rules for assessing the safety condition of workers based on given information. The first metric to consider is the degree of danger of a worker given hazard models and location data; if the worker is within the hazard envelope, it is considered as a near-miss event and the associated degree of danger is computed. The given information of hazards provides quantitative geometric information of identified hazards. Then, a rule/criterion is necessary to evaluate the degree of hazardousness of a worker when the worker is exposed to any of the identified hazards. The rule should reflect the level of proximity in a relationship that implies that the closer the worker is to the hazard, the higher chances the worker has to get involved in an accident. Figure 30 displays a three-dimensional (3D) linear model for the degree of hazardousness with a rectangular hazard. In developing rules, this model assumes that when the worker is found within a hazard core, the worker is considered to encounter an accident. In the meantime, the model assumes that the worker is safe if the worker is outside of a hazard envelope. The linear modeling uses indices to describe these cases: 1 for the case, "within the core", and 0 for the case, "outside the envelope." The intermediate zone between the core and envelope is measured by linear interpolation. The same rules apply to other cases of hazard models.

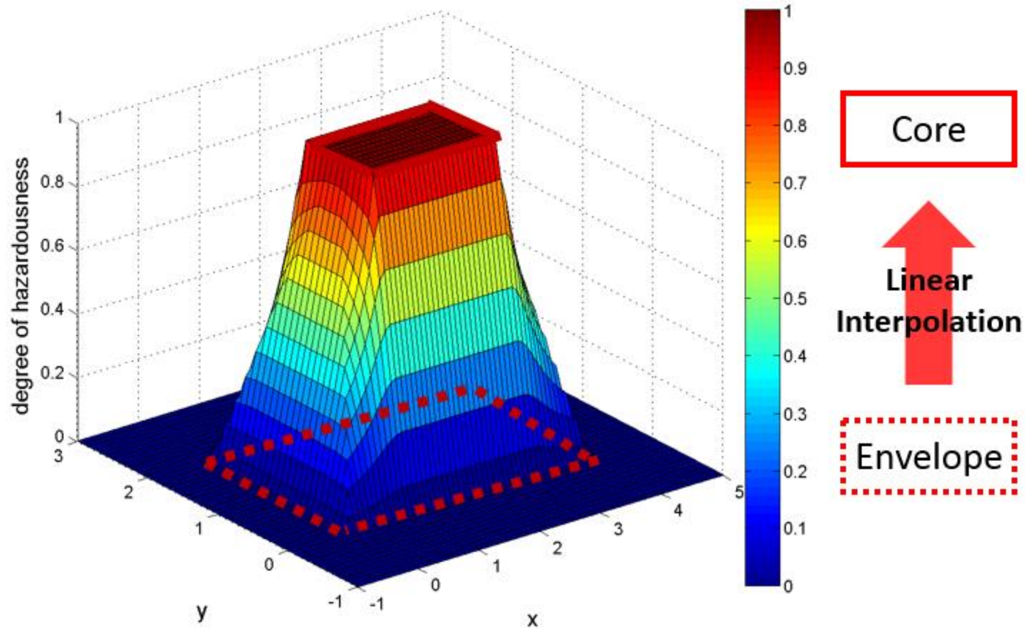


Figure 30: Linear modeling of the degree of hazardousness

Each construction activity/hazard presents various levels of danger; for example, a-fall-to-a-lower-level accident likely involves more serious damage to associated workers than a-trip-accident does. Despite this difference in potential damage, the method of introducing a safety envelope may not sufficiently cover the consequences caused by their potential damages. To take into account this effect, the ZBSR approach uses a scaling factor to intensify the degree of danger. The described procedure generates an index that indicates the rate of the occurrence of an accident per a specified time interval of update. Because it is a representation of the degree of dangerousness at a certain time interval and because the safety monitoring system continuously collects and generates such data over a period of time, the system aggregates all of the data and produces an safety performance index in various forms depending the inspector's needs.

7.3 Zone-based Safety Risk Analysis based on RTLS Data

This sub-section presents the ZBSR analysis, which incorporates the previously discussed components: the hazard modeling and the evaluation rules and criteria. This incorporation with a feed of real-time location data from on-site workers completes the development of the quantitative procedure, ZBSR, which translates contextual data (e.g., worker information and location information.) collected onsite into a quantitatively meaningful index representing the safety condition of individual workers. This translation factors in the understanding of workers' safety-related behaviors and conditions. The associated parameters in the ZBSR analysis may not be deterministically quantified because of uncertainties involved: the assumptions in the modeling of parameters lead to model uncertainties, while measured information/data contain measurement uncertainties. To account for variability/uncertainties, the ZBSR model takes on a probabilistic approach to combine the parameters and input data and evaluate the safety performance of a worker.

Equations 16 - 19 show a general overview of equations associated to ZBSR. The quantification of the safety performance involves the various parameters discussed as shown in Equation 16. As the location estimation by the tracking system is not deterministic, the position estimation is probabilistically evaluated on its accuracy based on the standard deviation of the system as shown in Equation 17; the ZBSR analysis uses a normal distribution for generating candidate particles (x_i, y_i) given the location estimation (x_{est}, y_{est}) and the standard deviation. Equation 18 shows the two types of hazard models and their associated parameters. Equation 19 presents the necessary parameters for computing the exposure level. ZBSR first finds the distances from the worker's claimed location (x_i, y_i) to the closest point of a hazard core (prox1) and that of a hazard envelope (prox2) and uses linear interpolation to quantify the degree of hazardousness, which is also known as the exposure level.

$$spi_i = f(loc_i, haz, expo, scale, freq) \quad (16)$$

spi_i = safety performance index for give location, loc_i
loc = location of position estimate
haz = hazard models
expo = exposure level/degree of hazardousness
scale = a scale factor
freq = frequency/exposure time

$$loc_i = f(x_i, y_i;\ x_{est}, y_{est}, std) \quad (17)$$

$$f(x_i|y_i) = f(x_i|y_i; x_{est}, y_{est}, std)$$

$$f(y_i|x_i) = f(y_i|x_i; x_{est}, y_{est}, std)$$

x_i,y_i = actually possible positions
x_{est}, y_{est} = position estimation from the system
std = standard deviation of the position estimation

$$haz = \begin{cases} f\left(length_{core}, width_{core}, length_{envelop}, width_{envelop}\right) \\ f(radius_{core}, radius_{envelop}) \end{cases} \quad (18)$$

$$exposure = f(x, y, haz, scale) = f(prox1, prox2, scale) \quad (19)$$

prox1 = distance to edge of hazard core
prox2 = distance to edge of hazard envelope

Given a location datum point of a worker (location estimation indicated by x_{est} and y_{est}) at a specific time interval, the ZBSR model checks all of the nearby hazards to comprehensively assess the safety performance. Equation 20 shows a general integral method that computes the safety performance index for a given location estimation and its uncertainty. However, the integral in the safety performance equation is for a continuous function, which is not the case for this analysis. Instead, Equation 20 is modified to a numerical summation so that the assessment is made in a discretized manner as shown in Equation 21. In the discretized version of the assessment, additional indices, j and k, are introduced; index j is to cover the situation where the worker is involved with more than one hazard, and index k is to aggregate continuously generated safety performance evaluations as the worker continues movements and the system yields the corresponding safety evaluations.

$$spi_{ZBSR} = \int spi_i = \int f(loc_i, haz, expo, scale, freq) \tag{20}$$

spi_{ZBSR} = safety performance index by ZBSR

$$\begin{aligned} spi_{ZBSR} &= \sum_{all\ i} spi_i \\ &= \sum_{all\ i} \sum_{all\ j} \sum_{all\ k} f\left(loc_i, haz_j, expo_{i,j}, scale_j, freq_k\right) \end{aligned} \tag{21}$$

i = index for each (x, y) location
j = index for hazards
k = time index

7.4 Experiments and Results

This section presents two sets of experimental studies that are sequentially developed. The first experimental study aims to test the capability of the BLE-based tracking system in detecting unsafe incidents through the ZBSR approach, while the second study, which is an extended version of the first test, is to test the capability of the hybrid-tracking system in quantifying the safety performance of workers based on detected unsafe incidents.

7.4.1 Experimental Study 1

This test involves a field experiment at an indoor construction site for evaluating the capability of the BLE-based tracking system in monitoring safety incidents based on a zone-based detection approach. For practical assessment of the system, the test is conducted at a complex indoor environment during construction operation hours. Figure 31 depicts the sensor deployment plan for the field testbed. The location of sensors and their coordinates are indicated in Figure 31; the density of BLE sensors is approximately one sensor per 28 m^2.

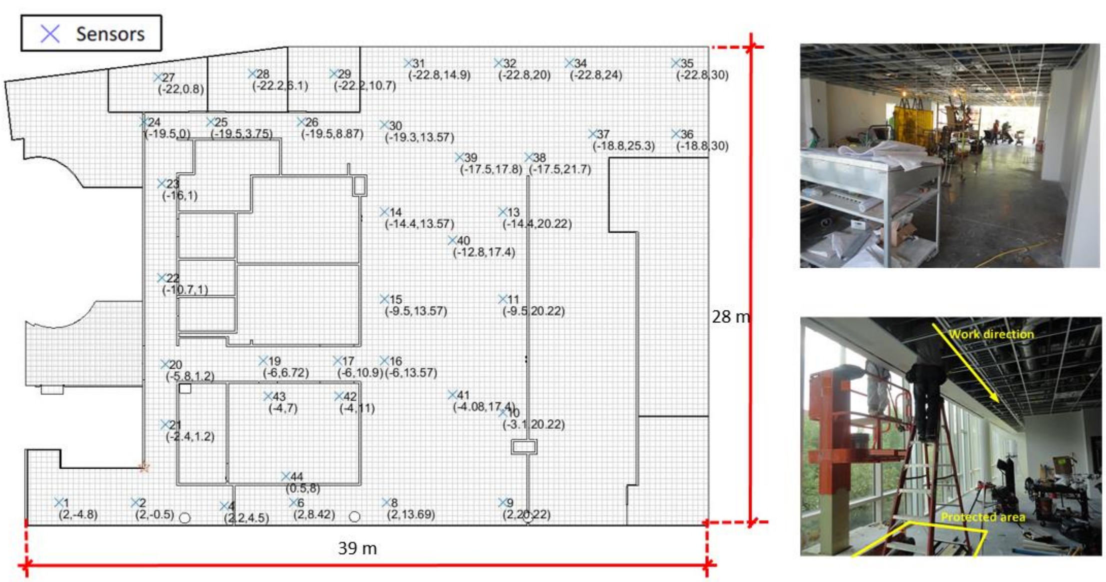


Figure 31: Sensor deployment and testbed

The daily work schedule and on-site inspection identify three hazards, which are registered in the system for monitoring of the interaction of workers with the hazards. Figure 32 shows the three hazardous areas and designed paths that are to simulate situations where certain violations occur. Each of the test subjects walks along each of the seven designed paths, which are specifically designed as follows:

- Path 1: the test subject passes through both the envelope and core hazard zones in Hazard 1. The designed path is 55 meters long.
- Path 2: the test subject passes through both the envelope and core hazard zones in Hazard 1. The route is different from Path 1. The designed path is 58 meters long.
- Path 3: the test subject approaches near Hazard 3 but does not breach into the hazard. The designed path is 46 meters long.
- Path 4: the test subject approaches near Hazard 3 but does not breach into the hazard. The route is different from Path 3. The designed path is 36 meters long.
- Path 5: the test subject passes through both the envelope and core hazard zones in Hazard 3. The designed path is 54 meters long.
- Path 6: the test subject passes through both of the envelope and core hazard zones in Hazard Zone 2 and then both the envelope and core hazard zones in Hazard 3. The designed path is 114 meters long.
- Path 7: the test subject passes through only the envelope zone in Hazard Zone 1. The designed path is 55 meters long.

The testing of such paths is particularly important because the metrics obtained from these tests are used to evaluate the performance of the system in certain aspects: 1) hazard detection test, 2) nuisance detection test, and 3) sensitivity test. It is worth noting that sensitivity analysis in this context is different from recall analysis (or true positive rate analysis). The sensitivity test in this context measures data that represent the capability of the system to detect the transition of the state of safety conditions, both from a safe zone to an envelope zone and from an envelope zone to a core hazard zone. The hazard detection tests involve an analysis of data collected from the tests of paths 1, 2, 5, 6, and 7, the nuisance detection tests involve paths 3 and 4, and the sensitivity tests involve paths 3, 4 and 7. The three sets of tests examine the reliability and effectiveness of the system in detection of hazard incidents in different situations.

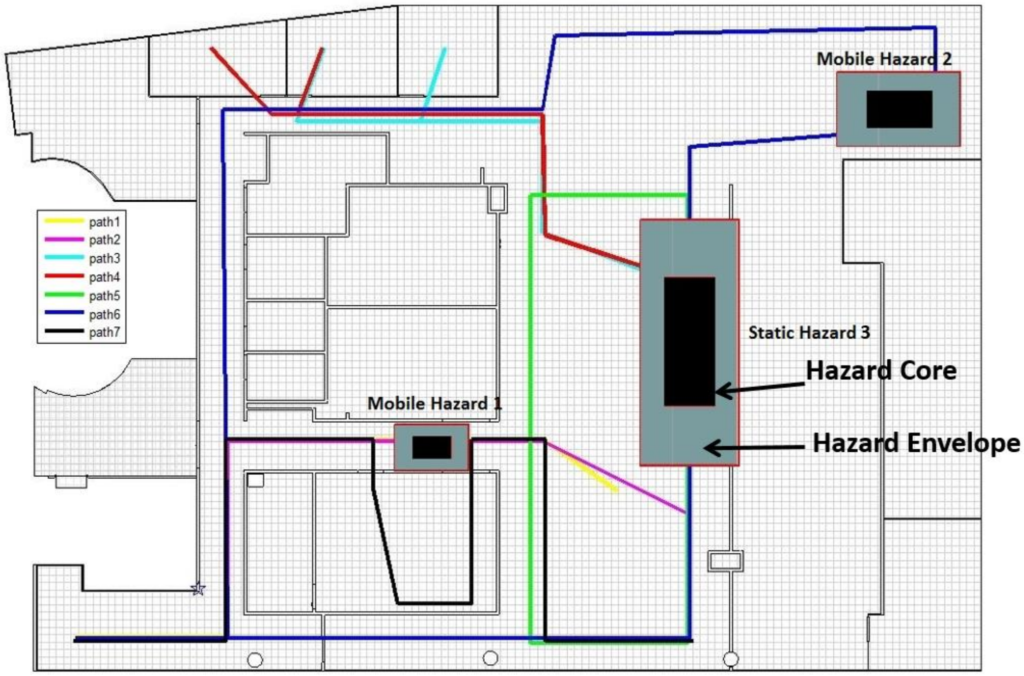


Figure 32: Test scenarios and associated hazards

The test on each path is repeated ten times by each subject, and the results are aggregated for analysis. Figure 33 plots one set of the ten trial sets on a separate plot for each subject. Although the trajectories contain a degree of fluctuation, which is inevitable with an absolute positioning system, the system captures most of the violations that have been committed by the test subjects. Figure 34 exhibits one particular case of violation detection by a test subject for detailed analysis. Automatically collected data from the site are presented in a 3D view as shown in Figure 34 (upper left). This view includes a detected hazard incident that is shown in Figure 34 (upper right). Scrutiny of the collected data reveals that this incident is first detected at 11:45:43 am on July 22, 2015, and ended at 11:45:52 am on July 22, 2015. This subject stayed in Hazard 2 for about nine seconds as the subject moved top to bottom inside the hazard zone; the associated coordinates are approximately the coordinates (-19, 29) and (-18, 24) for entrance and exit, respectively.

Figure 33: Plots of the test results for each subject

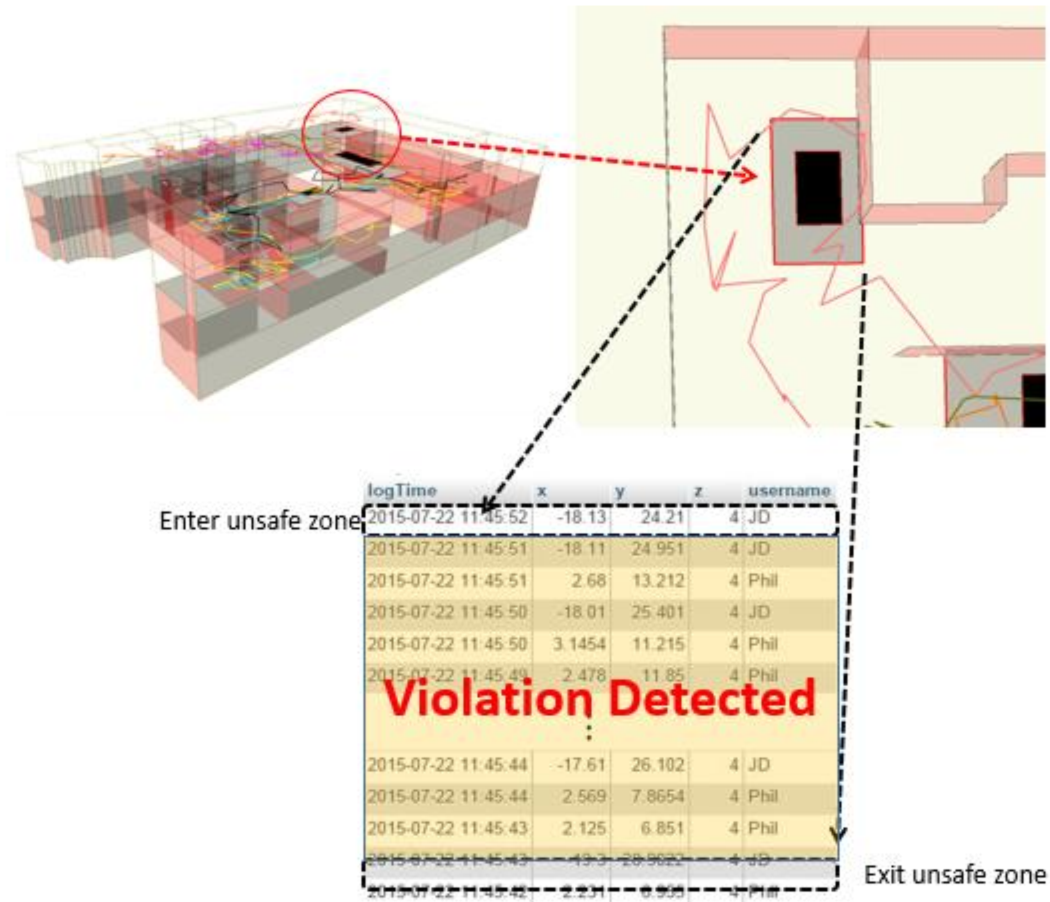


Figure 34: Details of a violation detection and its zoomed-in view

For each of the test cases, this research conducts a statistical analysis for true positive (TP), false negative (FN), true negative (TN), false positive (FP), recall and specificity. The classification criteria are set as follows:

- TP: an instance in which a subject in a core/envelope zone is detected
- TN: an instance in which a subject in a safe zone is not detected
- FP: an instance in which a subject in a safe zone is detected
- FN: an instance in which a subject in a core/envelope zone is not detected

- Recall (TP rate): Rates of correct detections among core/envelope instances; this value is computed as a fraction of the number of true positive over relevant events (Equation 22)
- Specificity (TN rate): Rates of undetected events among events that do not cause core/envelope instances; this value is computed as a fraction of the number of true negative over the events with no dangerous/caution instances (Equation 23)

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

$$specificity = \frac{TN}{TN + FP} \tag{23}$$

The core and envelope hazard zones are different by nature as one needs to be more strictly monitored than the other. To understand the detection capability of the monitoring system for these hazard zones, statistical evaluations are performed separately for the two hazard zones. Note that as four test subjects repeated ten trials for each path, the total value is obtained by multiplying the number of subjects, ten trials, and the number of hazards in each path; the associated equation and the actual computation in a matrix form are shown in Equations 24 and 25.

$$TNT = NS \times NT \times NH \tag{24}$$

TNT = total number of trial
NS = number of subjects
NT = number of trials
NH = number of hazards in each path

$$TNT = \begin{bmatrix} TNT_{path1} \\ TNT_{path2} \\ TNT_{path3} \\ TNT_{path4} \\ TNT_{path5} \\ TNT_{path6} \\ TNT_{path7} \end{bmatrix} = 4 \times 10 \times \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 40 \\ 40 \\ 40 \\ 40 \\ 40 \\ 80 \\ 40 \end{bmatrix} \tag{25}$$

Table 8 summarizes the above classification criteria for the cases in which the subjects interact with the hazard cores, and Table 9 does the same for the cases in which the subjects interact with the hazard envelopes. The criteria for each path depend on the type of movement involved in the path; if the designed path breaches into a core/envelope hazard zone, then this case is associated with the following criteria: TP, FN, and recall; if the designed path does not breach into a core/envelop hazard zone, then this case is associated with the following criteria: TN, FP, and specificity.

If the subject is within an envelope hazard zone, the subject is considered to be at risk. This risky condition can be assessed through recall analysis, which provides the reliability measure of the safety monitoring system with respect to the breach incident. For most of the cases, the tables show that the system indicates a fairly accurate detection rate of recall with 69% at the lowest, 100% at the highest, and 90% on average. Comparing the recall values from Table 8 and those from Table 9, the system tends to be more reliable in detecting the breach when the safety envelope zone is violated than in detecting the breach when the core hazard zone is violated. This is a reasonable observation since the breach into the safety envelope zone requires more coarse accuracy of positioning than the core hazard zone does. To eliminate any potentially unsafe events, which are considered near miss events and may lead to accidents, the detection of breaches into safety envelope zones (indicated by Table 9) is of the utmost importance (Li et al. 2016). In this aspect, the performance of the system is considered satisfactory with a recall rate of about 98%.

The specificity analysis evaluates the performance of the system on the transition of the hazard boundaries. That is, this analysis involves certain scenarios (i.e., paths 3, 4, and 7) that the designed paths almost crossed the boundary on which the transition of the state occurred (e.g. from a safe zone to an envelope zone, or from an envelope zone to a core hazard zone). Because of the highly sensitive characteristic of the transition, a small error in position can lead to a false detection of safety incident. Compared with the results of the recall analysis, those of the specificity analysis show a larger variation and a lower accuracy. Despite this relatively low reliability, this finding seems reasonable as such a test constitutes much more strict criteria.

Table 8. Statistical analysis for the hazard cores

Analysis metrics	Path						
	1	**2**	**3**	**4**	**5**	**6**	**7**
True positive	29 / 40	39 / 40	NA	NA	40 / 40	55 / 80	NA
False negative	11 / 40	1 / 40	NA	NA	0 / 40	25 / 80	NA
True negative	NA	NA	40 / 40	40 / 40	NA	NA	3 / 40
False positive	NA	NA	0 / 40	0 / 40	NA	NA	37 / 40
Recall	72.5%	97.5%	NA	NA	100%	68.8%	NA
Specificity	NA	NA	100%	100%	NA	NA	7.5%

Table 9. Statistical analysis for the hazard envelopes

Analysis metrics	Path						
	1	**2**	**3**	**4**	**5**	**6**	**7**
True positive	39 / 40	39 / 40	NA	NA	40 / 40	79 / 80	39 / 40
False negative	1 / 40	1 / 40	NA	NA	0 / 40	1 / 40	1 / 40
True negative	NA	NA	22 / 40	23 / 40	NA	NA	NA
False positive	NA	NA	18 / 40	17 / 40	NA	NA	NA
Recall	97.5%	97.5%	NA	NA	100%	98.8%	97.5%
Specificity	NA	NA	55%	57.5%	NA	NA	NA

7.4.2 Experimental Study 2

Experimental test 2 involves two sets of field experimentations for testing the ZBSR models in quantifying the safety performance of a worker who is often exposed to hazardous areas. For safety reasons, this test has been conducted in a controlled environment with a trained subject; the test emulates certain safety incidents and violations that can control the safety condition of the site. The controlled movement, which serves as the ground truth, provides a benchmark for comparison with the results acquired through the location tracking system. Figure 35 and Figure 36 show the two test beds and the associated hazard areas. This validation assumes that the tracking system has been verified to have an accuracy of approximately 1.5 meters as has been demonstrated in CHAPTER 6. This accuracy is used as the uncertainty of the tracking accuracy when processing the ZBSR model for quantifying the safety performance of the test subject. Because this experiment uses the demonstrated tracking system, information associated with the tracking system are neglected in this context.

Figure 35: Testbed 1 and its hazard area

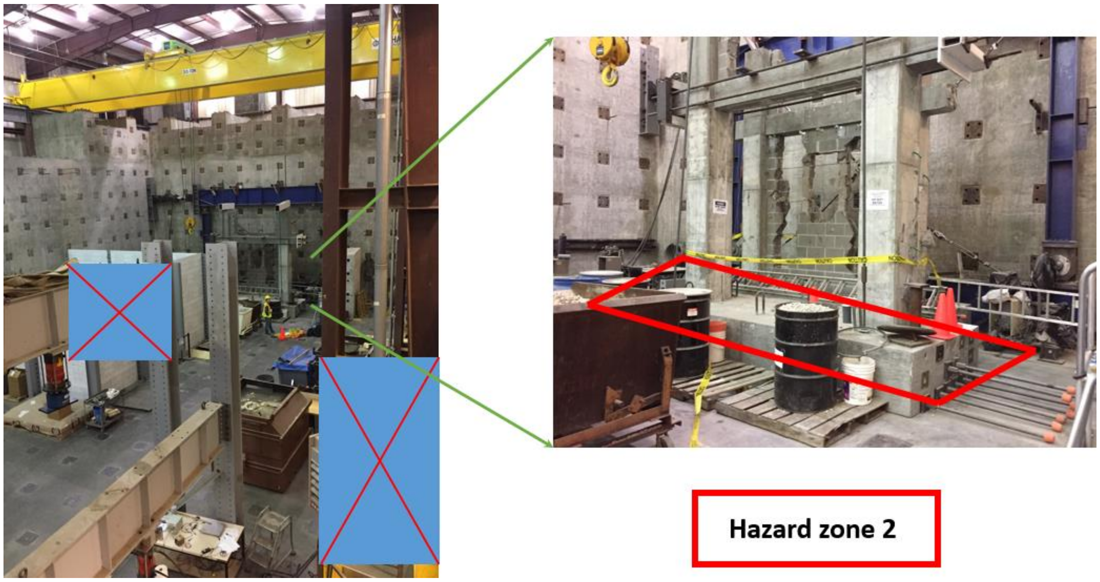


Figure 36: Testbed 2 and its hazard area

To create cases that represent various degrees of proximity level, exposure time, and exposure frequency, the study designs a multitude of scenarios in the two testbeds. Figure 37 shows the scenarios for each of the testbeds. Based on the designed scenarios, the subject passes through a hazard zone and/or stays in/out of a hazard zone. The deployed tracking system collects the location information of the subject. Then, the safety system applies the ZBSR model to analyze and interpret the data to assess the safety performance of the subject in the form of a safety index.

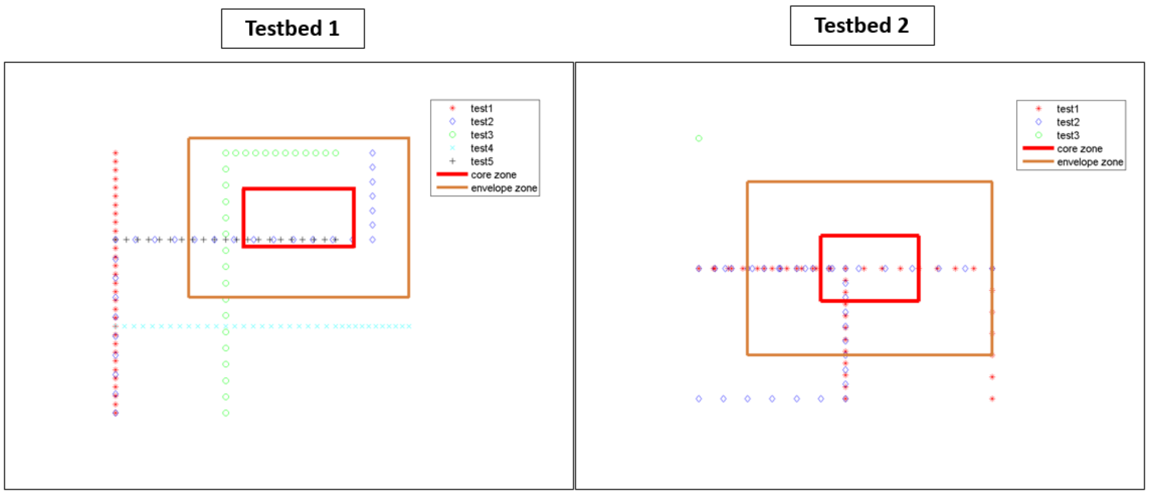


Figure 37: Test scenarios

Figure 38 exhibits the tracking results and the corresponding ground truths of scenario 2 in testbed 1 and scenario 2 in testbed 2; the arrows indicate the direction of movement in the paths. Once the tracking data are collected, the system feeds them into the ZBSR model for analysis. Because of the uncertainties discussed previously, the safety performance is probabilistically assessed by applying Equations 16 to 21. ZBSR first receives the streaming of position estimation—it takes each of the estimated points individually into the analysis— and associates the estimation with the hazard models registered in the system. After processing the position data through the equations, the probabilistically assessed safety performance is generated.

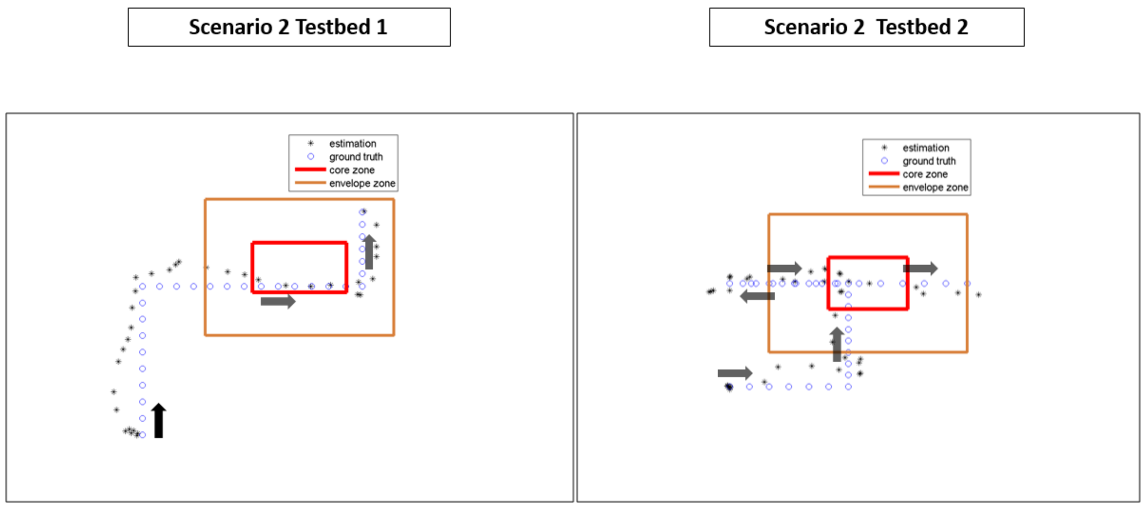
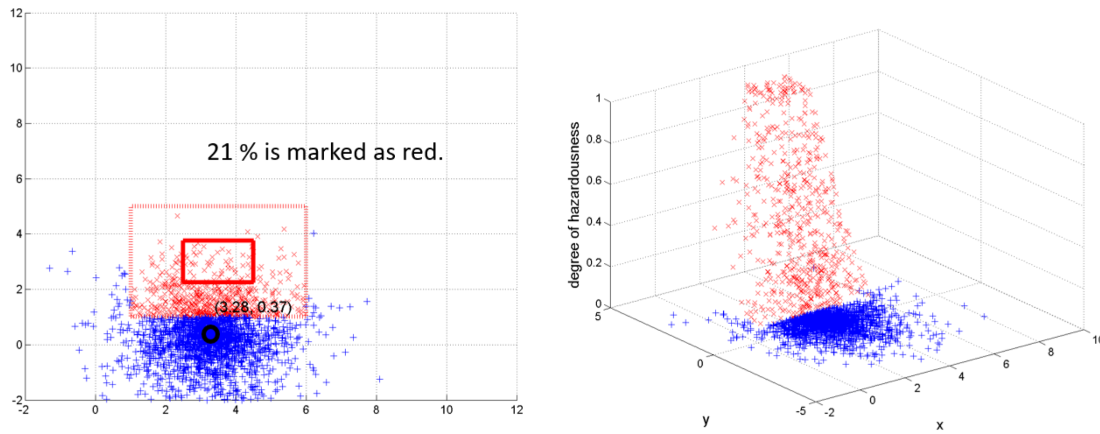
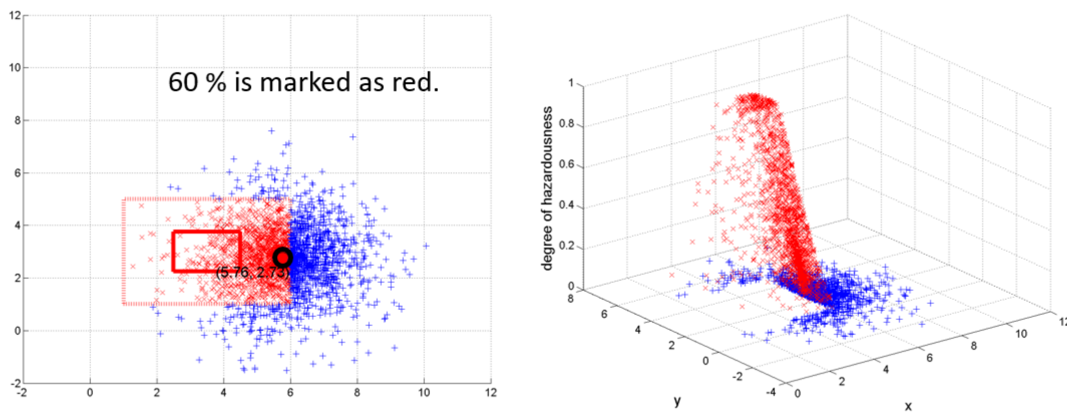


Figure 38: Tracking results and the corresponding ground truths of certain test cases

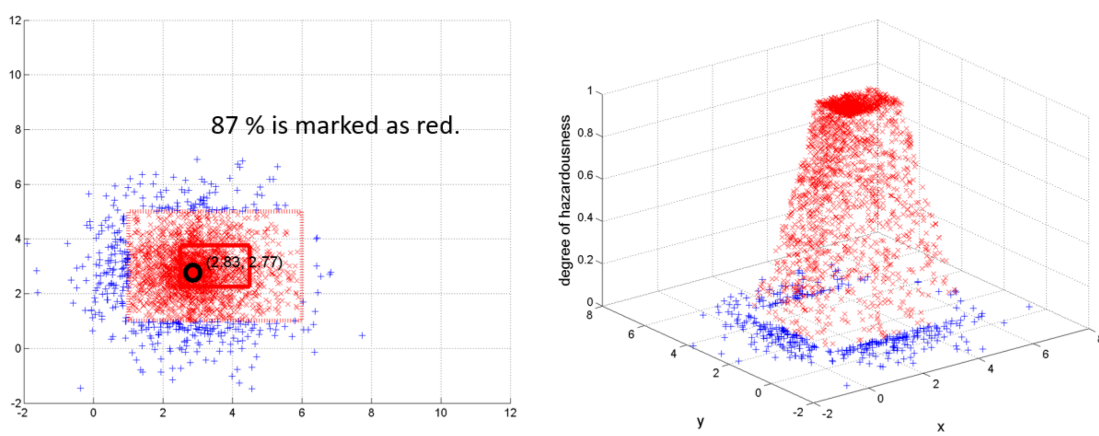
Figure 39 selects three points from scenario 2 in testbed 2 that uniquely describe the situation; the first point shown in Figure 39 a) represents the case of safety assessment when the subject is near the hazard zone but does not invade the zone; the second point shown in Figure 39 b) represents the case of safety assessment when the subject is in the hazard core; the third point shown in Figure 39 c) represents the case of safety assessment when the subject is inside the hazard envelope but outside the hazard core. The observation of the number of points in each of the hazard zones seems reasonable because the increasing number of points from case a) to case c) properly reflects the increasing proximity level; the numbers of points are 21, 60, and 87 % for the cases a), b), and c), respectively. The right figures for each of the cases in Figure 39 plot the hazardous degree of each of the (x, y) points based on the linear model discussed in Section 7.2. The plots yield congruent results with the previous observation. As the position estimation advances towards the core of the hazard zone, the number of points in a high scale increases.



a) Evaluation of a point outside the hazard zone



b) Evaluation of a point inside the hazard envelope but outside the hazard core



c) Evaluation of a point inside the hazard core

Figure 39: Evaluation of sample points from Scenario 2 of Testbed 2

To provide a better insight of the degree of hazardousness, Figure 40 shows 2D projections of the right 3D plots in Figure 39 by converting the projected (x, y) coordinate to the number of data point. The plot representing the point outside the hazard zone contains sporadic data points that are greater than a hazardousness score of 0 while having a large portion of points that are equal to a hazardousness score of 0. This trend (hazardousness level) changes as the subject moves towards the hazard area. When the subject is estimated to be in the hazard core, the corresponding plot contains a large portion of points that are equal to or greater than a hazardousness score of 0.5. In sum, the graphs indicate that higher scores are more frequently observed as the subject moves from outside of the hazard zone to inside the hazard envelope and from inside the hazard envelope to the hazard core.

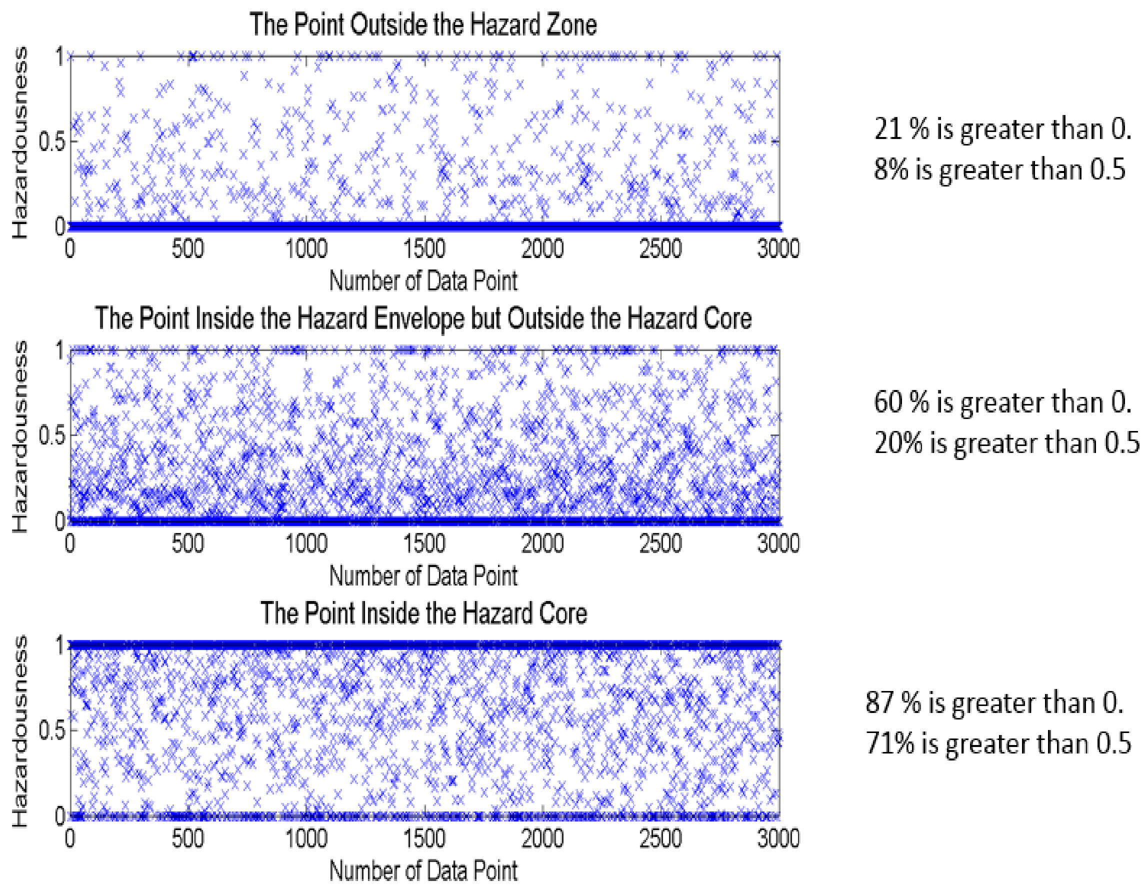


Figure 40: Detailed assessment of each of the evaluations

So far, this chapter has introduced the assessment of each point based on the developed models and equations. Because each of these (x, y) points are probabilistically assessed, each point has its own likelihood of occurrence at a rate of one per the number of data point, which in this case is 1/3000. After taking into account this likelihood of each datum point, the safety index is computed as shown in Equation 21. Note that the description made herein focuses on the selected three points, but the safety evaluation system processes all of the estimated points—in our example, the estimated points are the points illustrated in Figure 38— and yields the assessed safety performance indices for the points. Figure 41 presents the results of the ZBSR analysis for scenario 2 of testbed 2 with respect to the safety performance index, which represents well the safety condition of the test subject. Scrutiny of the data in Figure 41 reveals the following summary:

- The subject is in the safe area until about 10 seconds
- From about 10 seconds, the subject is exposed to a low level of hazardousness
- From about 17 seconds, the level of hazardousness spikes up
- The subject is detected to stay in the hazard from about 20 seconds to 25 seconds
- From about 25 seconds, the level of hazardousness drops to almost zero at about 28 seconds
- The subject is detected again in the hazardous zone, and the level of hazardousness spikes up from about 35 seconds
- The subject is detected to stay in the hazard from about 36 seconds to 40 seconds
- From about 40 seconds, the level of hazardousness drops and the safety hazard condition disappears

These summaries agree with the actual movement of the subject simulated in scenario 2 in testbed 2. In addition, the results not only describe the behavioral phenomena of the subject but also quantifies the safety performance of the subject based on the given hazards and their associated modeling information.

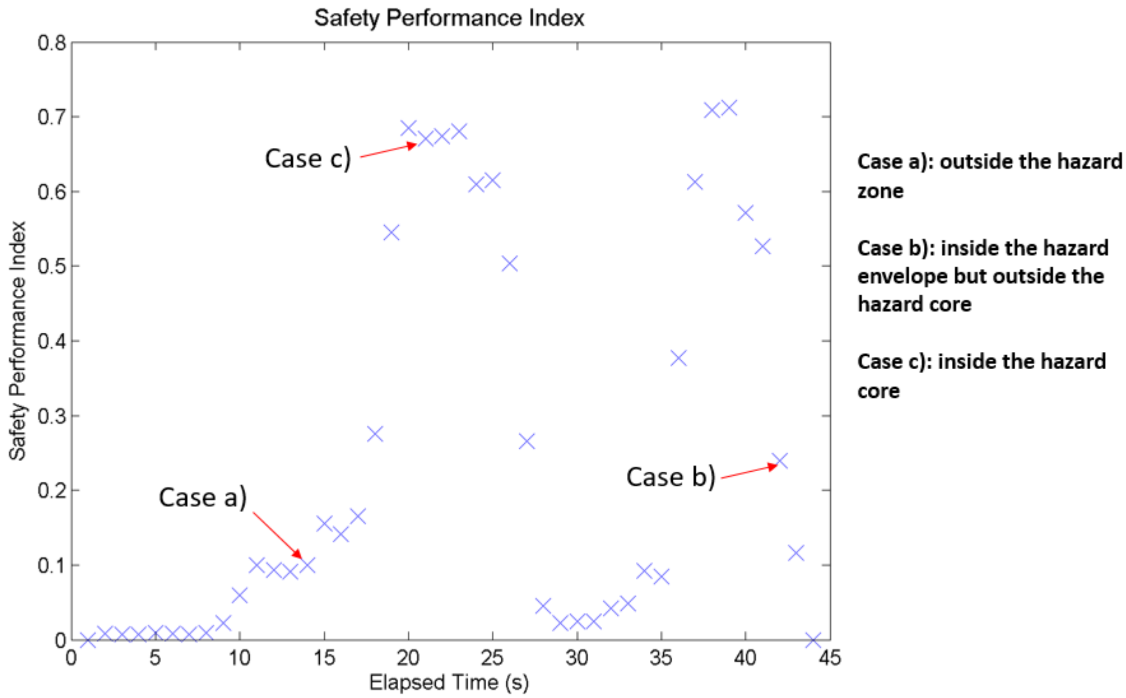


Figure 41: Safety performance index for scenario 2 of testbed 2

To compare the safety performance index (SPI) resulting from the test data with that resulting from the ground truth, the same analysis is conducted on the ground truth data set. Figure 42 plots the SPI in a compact scale for each of the two cases: the test case and the ground truth case. Overall, the SPI of the test case seems capable of reflecting the safety condition of the subject as it represents relatively well the trend of the SPI. One of the intriguing findings from the observation of the results is that the SPI of the test data underestimates the safety condition of the subject when compared with the SPI based on the ground truth data. Although this is not a desirable observation, it is inevitable because of the uncertainty of the associated parameters. The difference between them is partially explained by using a sample data from Figure 39. Figure 39 c) shows scattered data points that are extracted from a given position data set. These scattered points indicate possible locations with unique weights assigned to them. In this case, because it is a probabilistic approach with the scattered points, the procedure uses not only points within the core but also points in the envelope area as well as in the safe area. However, in the case of using the ground truth, because it is a deterministic measure, the SPI is computed to be one. Resulting from these differences, the lower SPI by the system is inevitable: the SPI from the test data set is 0.251 for the test time period while that from the ground truth is 0.330.

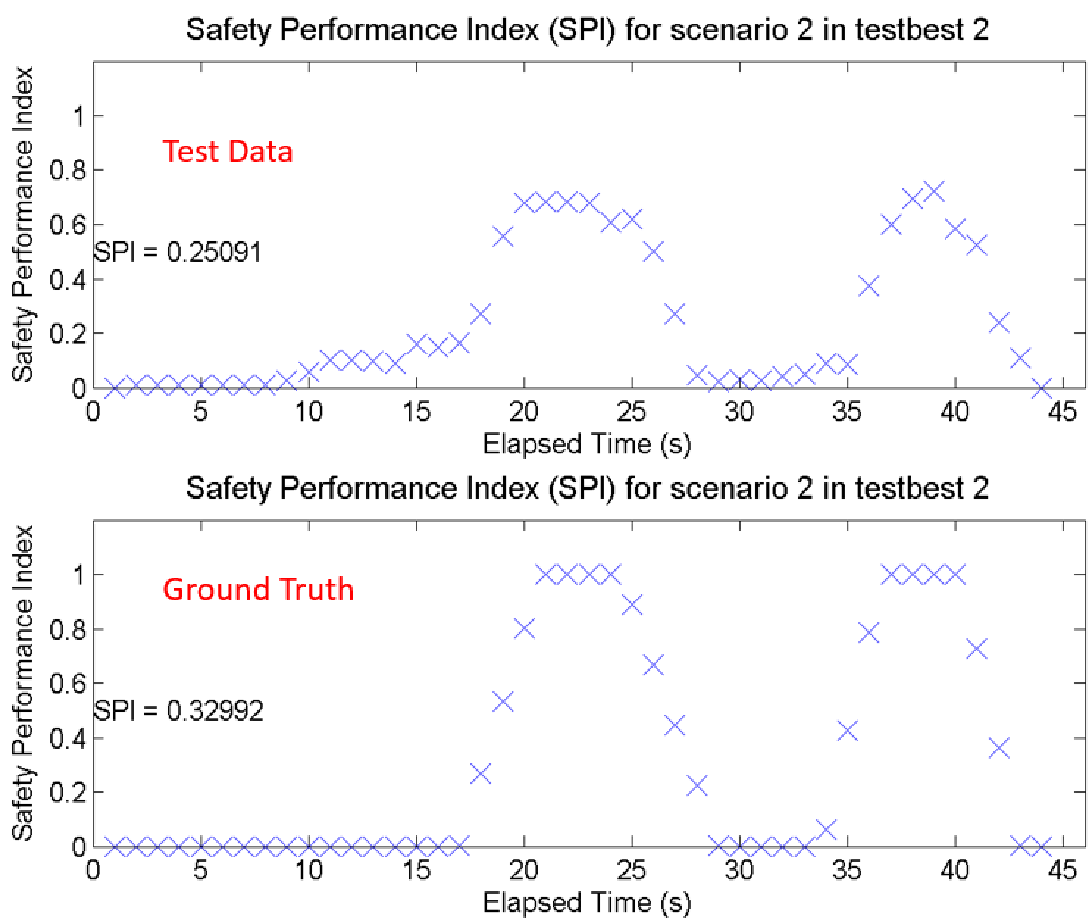


Figure 42: Safety performance index comparison

Table 10 lists the results of the comparison between the test data and the corresponding ground truth data. Certain cases (scenarios 1 and 4 in testbed 1 and scenario 3 in testbed 3) that simulate a safe situation but near the hazard envelope lead to fairly accurate estimation of the safety condition as the differences between the SPIs of the ground truths and that of the test data sets are close. The other cases in which certain unsafe movements are observed result in similar findings as discussed above. Note that the SPI values are based on the duration of data collection, so the SPI values continuously change with the data feed in the following analysis.

Table 10. Comparison of the aggregated safety performance index of the ground truth and that of test data

Testbed	Scenario	SPI of ground truth	SPI of test data
1	1	0	0.0024
	2	0.328	0.221
	3	0.253	0.295
	4	0	0.028
	5	0.619	0.506
2	1	0.390	0.291
	2	0.330	0.251
	3	0	0.009

7.5 Chapter Summary

The construction industry has suffered from inefficient methods of conducting safety-related inspection and analysis with limited resources. To overcome this challenge, this study developed a framework for an automated safety monitoring system and presented a new analytical and computational method for evaluating the safety performance of workers through the ZBSR model. To assess the performance of the development system and model, two sets of experimental studies were conducted in different construction sites.

Through the first set of experimental studies, the system demonstrated that the zone-based approach was accurate enough to detect workers' violation into pre-defined hazard zones. The results of the statistical analysis indicated that the system—for the tested environmental setting—acquired a recall rate of approximately 80% for the detection of a hazard core violation and approximately 98% for the detection of a hazard envelope violation. The second set of experimental studies assessed the reliability and effectiveness of the ZBSR model for quantifying the safety performance index of workers with respect to pre-identified and registered hazards. The various test scenarios and setups simulated diverse conditions that vary the conditions of the parameters that affect the quantification of the safety index. The test results showed clear evidence of the system and model's capability in describing the safety conditions of workers with respect to nearby hazards based on the given location data from the tracking system. This approach presented an innovative way to provide information on an unprecedented level to the project manager or safety manager regarding individual workers' safety performance. The approach is advantageous over conventional methods because it can offer impartial, automatic (or semi-automatic), and continuous job safety analysis/plan and eliminate problems related to workers' safety stemming from the lack of understanding of the safety performance of individual workers.

CHAPTER 8. CONCLUSION AND DISCUSSION

This chapter summarizes the research findings and discusses their potential contribution. The discussion of the limitations of the current research and the future research follows.

8.1 Summary

The construction industry has not been successful at protecting workers by exercising current safety practices. The current safety practices mainly rely on human efforts, which are fragmented, subjective, and inconsistent, and these challenges result in difficulty in handling on-site safety issues in a dynamically evolving site. Because of these, engineers/safety managers are often unable to identify/recognize safety issues that can translate to potentially hazardous events that, in turn, escalate to injuries and fatal accidents. In other words, the current method of data collection is ineffective and do not provide information on a sufficient level to safety managers and engineers. This has limited our understanding of individual workers' safety performance and the overall safety performance of the project.

To form a structural basis of research objectives, the dissertation conducted a thorough literature review and identified specific research/knowledge gaps as follows: 1) lack of reliable and effective tracking/monitoring methods for an indoor construction environment, 2) lack of comprehensive methods for data collection for safety evaluation at an individual level, 3) lack of a formal method that analyzes the safety condition of workers, and 4) lack of a framework that integrates all necessary processes (from site monitoring to analysis for quantifying the safety performance of individual workers.

To close the research gap and thus to understand the safety performance of individual workers, the dissertation presented a framework for performing automatic data collection (without manual measuring efforts of human) on site, transforming these data into meaningful information, and processing the information through the zone-based risk analysis model for assessing the safety performance of workers. To achieve these research goals described in the framework, the study presented two tracking-methodological developments and a method for assessing the safety performance of workers using tracking data.

To validate the research developments of the dissertation, several experiments were conducted at multiple construction sites in controlled settings for safety purposes. The first experiment focused on testing the developed PLS algorithm by comparing it with common localization algorithms. The results of the tests showed strong evidence that PLS outperforms the compared algorithms especially in an environment, where significant environmental conditions that cause signal interference exist. The second test proved that the hybrid-tracking approach, which integrates BLE, IMU, and BIM, yielded clear improvements of the tracking performance in accuracy and reliability. In addition, the knowledge-based error correction method in the integration demonstrated the ability to fix errors found in each of the sensors. The third test validated the effectiveness of the ZBSR models for quantifying the safety performance of workers. The various test cases indicated that the analysis could reflect the safety conditions of workers tracked by the ground truth data and determine the safety performance of workers in a quantitative form of measurement—safety performance index—,which has not been available in the industry.

8.2 Research Contributions and Impact

The findings of the study contribute to the body of knowledge in several ways: 1) the PLS algorithm and the associated methodological developments presented a way to overcome the fragility and unreliability of radio signals at a noisy, complex indoor environment, which leads to difficulty in localization; 2) the hybrid-tracking approach presented an effective-integrated method for indoor tracking; 3) the associated methodological developments in the hybrid-tracking approach suggested a technical approach—by presenting knowledge-based error correction method—to correct errors in each of the sensors, which have been persistent problems when the sensors are used independently; 4) the safety procedural developments bridged on-site data collection and safety analysis processes; and, 5) the index data of safety performance provided safety-related information on an unprecedented level that has not been available in the industry.

8.3 Limitations and Future Research

Although this research presented many methodological developments in each of the methodology chapters, it has a few limitations that may be studied in future research. The BLE sensors and its deployment plans should be coordinated together with construction schedules and other associated information. During the experimentation, it was found that the deployment plan may not be carried out as desired by the user because it may conflict with the movement of workers and their working directions. The tracking components require calibration and the results of calibration have noticeable influence on the accuracy of the tracking components. Because the knowledge-based interaction is acquired from good results of at least one component, the system may not perform comparably when all components are not properly calibrated and do not yield good results. The ZBSR model in this research was limited to deal with certain types of hazards that can be defined through geometric information for modeling. Because of this scope, the evaluation of the safety performance index is not the reflection of safety evaluation on all safety issues on site. As stated, the evaluation excluded hazards to workers while they are on the job (e.g., cutting fingers, falling from a ladder, equipment operation mistakes, electrocution). These hazards present different characteristics that cannot be modelled by geometric information to capture any safety incidents associated with them.

Future research should consider the rapid development of sensing technologies. This research utilized relatively inexpensive sensors and acquired promising results even with these sensors. The results can be further improved if more sophisticated and refined sensors are used in the system. For example, if motion sensors that are equipped with self-calibration capability—these cost several thousand dollars per device—are used in the system, the correction mechanism can be more reliable, thus producing improved results. Another aspect that future research can consider is to add zone-based presence detection technique by introducing additional tags around the hazard zone. As this will enhance the ability of zone-entrance/exit detection, the reliability of the violation quantification will be improved. Also, with technological development in the sensing domain, a new version of Bluetooth Low Energy, which is BLE version 5, has been released. This is expected to lead to performance improvement in the radio signal itself, so the adoption of this technology can also enhance the performance of the system in various aspects. For the aspect of the safety evaluation, future research should consider different methods for handling the excluded hazards.

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VITA

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